

INFORMED INSTITUTIONAL TRADING  
AND NEWS ANNOUNCEMENTS

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# INFORMED INSTITUTIONAL TRADING AND NEWS ANNOUNCEMENTS

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This dissertation studies the daily institutional investors trading patterns before and after public news announcements in the US equity market, such as Merger and Acquisition announcement and release of macroeconomic indicators. Do institutional investors have inside information, or do they have superior models before news announcement? Using a high frequency institutional trading dataset that combines intraday NYSE Trades and Quotes (TAQ) data with the quarterly institutional ownership report (13F) by a reduced-form model, this dissertation tests the hypothesis of institutional investors trading on inside information 1993 to 2004. I find that most institutional investors are informed traders who accumulate shares before good news or before takeover announcements as early as 30 days ahead. Institutional investors do not have superior models in that they only buy the actual future targets and sell the forecasted “rumor” stocks from an acquisition probability model. By reversing their positions on and after the announcement day, they realize positive profits. Further, I confirm that the pre-event trading pattern of institutional investors is associated with stocks that have high probability of informed trading.

## BIOGRAPHICAL SKETCH

Guohua Li was born on October 27, 1977, in Shandong province, People's Republic of China. She earned her Bachelor's degree in Economics in 1999 from People's University of China. In 2000 she came to the United States to pursue her graduate study and earned her Master's degree in Agricultural Economics with a minor in Statistics from University of Missouri – Columbia in 2003. She came to Cornell University in the fall of 2003 for her Ph. D study in the field of Applied Economics and Management.

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## CHAPTER 1

### INSTITUTIONAL TRADING AROUND MERGER AND ACQUISITION ANNOUNCEMENTS

#### 1.1 Introduction

*“We certainly see institutional-type accounts that have come into the market with extraordinarily good timing on a repeat basis; we have investigated those. But to get the evidence to prove a violation of the statute under which we allege insider trading is difficult.”*

- Joseph J. Cella, Chief of the Office of Market  
Surveillance at the US S.E.C., August 2006

The US financial market has long had strict insider trading laws to restrain such behavior and insure market fairness and integrity<sup>1</sup>. However, it is a difficult task to find empirical proof of illegal behavior, especially when it is difficult to distinguish it from legitimate market participation. An article in the August 27, 2006 edition of the *New York Times*, titled “Whispers of mergers set off suspicious trading,” describes an investigation by an analytical research firm, Measuredmarkets Inc., of the nation’s largest mergers over a 12-month period. Its results show that the securities of 41 percent of the companies receiving buyout bids exhibited abnormal and suspicious

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<sup>1</sup> Bhattacharya and Daouk (2002) have shown that insider trading increases cost of equity in many countries, and that the enforcement of insider trading law decreases cost of equity.

trading in the days and weeks before those deals became public.

Section 13(F) of the Securities Act of 1934 (1978 amendment) requires institutional investment managers with investment discretion of \$100 million or more of certain equity securities to disclose equity holdings on the final day of each quarter. According to the SEC, “The purpose of this disclosure requirement is to collect and disseminate to the public information about the holdings and investment activities of institutional money managers in order to assist investors, issuers and government regulators.”<sup>2</sup> Such information can be used by the SEC to analyze the influence and impact of institutional investment managers on the securities market. As Joseph Cella of the SEC points out, institutional-type investors are among the major concerns of security market investigators for possible non-legitimate trading based on material non-public information<sup>3</sup>. However, the low frequency of this quarterly filing requirement makes it difficult to capture any suspicious quick entry-and-exit executions by institutions in a short term. This is especially true in the case of corporate specific events where short-term profits are significant, such as merger and acquisition announcements, earnings announcements, changes in dividend policy and seasonal equity offerings.

Among all corporate events, Merger and Acquisition (M&A) are particularly interesting because they are supposedly unknown to the market, apart from a small group of insiders, before they are announced. In a takeover bid, the acquiring firm usually pays a high premium to buy the target firm stocks. The potential profits drive a

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<sup>2</sup> In the Matter of Quattro Capital Management, LLC, August 15, 2007.

<sup>3</sup> A report of SEC shows that in prosecution of insider trading and market-timing cases, 25% cases are institutions and 75% cases are individuals.

substantial amount of efforts to collect information and predict possible takeover targets. Results in this paper also show that predicting takeover targets will not make money unless you know exactly which one is going to be acquired. Institutional trading on possible future targets such as rival firms shows that institutions sell these targets and only buy the target firms that actually are taken over in the future 30 to 40 days.

Usually takeover deals involve companies, management-led buyout teams, private equity firms, large shareholders, and brokerage firms which have diverse businesses under one roof. Institutional investors are well-positioned to gain access to these information venues; therefore, any significant trading patterns a priori are suspected of capitalizing on inside information. Results of this paper show that there exist serial leaders such as brokerage firms who can consistently identify future target firms and accumulate shares in advance, a phenomenon that is consistent with their business position and information venue.

Previous studies on M&A document price run-ups and increased trading volume of target firms before announcements; however, it is still debatable whether pre-announcement trading involves trading on insider information or legitimate market participation. Keown and Pinkerton (1981) find that the abnormal returns prior to announcements are related to inside information leakage. Meulbroek (1992) observes a positive link between target firm price run-ups and days of prosecuted insider trading. Jarrell and Poulsen (1989) investigate pre-bid run-up from 1981 to 1985 and conclude that pre-bid market activity is mostly due to rumors. An immediate question is: who are responsible for the price and volume run-ups prior to takeovers –

institutions, individuals, or corporate insiders? Barclay and Warner (1993) find that medium-sized trades contribute to most of the price impact prior to takeovers. Chakravarty (2001), using a sample of NYSE firms, also finds that medium-size trades, which come from institutional investors, are most informative. Griffin, Shu and Topaloglu (2007) document that, in NASDAQ-listed target firms, individual investors build up net buying positions, while institutions mostly provide liquidity before takeovers. My paper provides empirical tests on whether institutional investors are well-informed prior to takeover bids by investigating their trading behavior before and after M&A announcements, for all target firms listed on the NYSE and AMEX from 1993 to 2004.

Specifically, I address five issues in this paper: First, do institutional investors exhibit significant trading imbalances (buy-sell) before and after M&A announcements? Second, I examine whether the abnormal trading volume by institutions is market participation or profit exploitation. If there is market-wide information leakage prior to the event, I expect to see immediate price jumps that incorporate such information, in which buyers of target firms are legitimate market participants. However, if there were no significant price jumps in the target firm stocks a priori – therefore no market-wide information leakage – any significant accumulation of target firm stocks by institutional investors becomes suspicious.<sup>4</sup>

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<sup>4</sup> We are not saying that a run-up pattern in CAR is not consistent with a market where informed trading exists. In reality, the run-up that we observe in the sample with all firms is probably due to informed trading and rumors/leakage. Moreover, when we talk about "market-wide information leakage", we are not talking about everyone knowing for sure that you will have an M&A, in which case you will indeed have "an immediate jump in the price". Rather, when we say "market-wide information leakage", we are talking about rumors which will lead to a run-up as some uninformed traders start speculating on the possibility of an M&A. Most of those uninformed traders end up losing money since many M&A rumors turn out to be incorrect (Gao and Oler (2007))

Third, which types of institutional investors are more likely to learn material non-public information – banks, mutual funds, brokerage firms, or insurance companies? Fourth, how do we distinguish institutions trading based on inside information from trading on their superior models? Can we further identify suspicious serial leaders who can consistently predict future M&A deals? Finally, is the significant front-running pattern of institutional investors associated with higher degree of information asymmetry among target firms? I use the probability of informed trading (PIN), developed by Easley, Kiefer and O'Hara (1997), as a proxy to measure the degree of information asymmetry and relate this PIN measure to the cross-sectional level of institutional trading imbalances over the event period.

The major findings of this paper are as follows: First, institutional investors start to accumulate shares in target firms as early as 30 trading days before an event, with statistically significant buying positions starting around day (-16). Average institutional abnormal net buying orders, as measured by daily net imbalances in excess of the average daily net imbalances over the entire sample period, have an arch shape over a [-30, +40] day window. Normally we expect investors to sell their stocks immediately on an announcement day to cash in, but, among all institutional investors, brokerage firms mostly act as merger arbitrageurs who either hold their positions or buy more shares on and after the event day, to speculate on the final deal consummation. By doing this, merger arbitrageurs provide liquidity at a market price that is lower than the proposed acquiring price, due to the possibility of takeover failure.

On an announcement day, most institutional investors (except investment

advisors) immediately reverse their trading positions to capitalize on their prior information, a pattern that is consistent with the theoretical model developed by Hirshleifer, Subrahmanyam and Titman (1994), in which some investors receive private information before others. In their model, “in a partially revealing rational expectations equilibrium, investors who discover information early trade aggressively in the initial period and then partially reverse their trades in the next trading round, when the trades of the investors who become informed at this later date cause the price to more fully reflect the investors’ information.” This paper provides empirical evidence for their model, in which institutional investors reveal the pattern of early informed investors who are “short-term profit takers”. Just as Cella from S.E.C market surveillance points out, “We certainly see institutional-type accounts that have come into the market with extraordinarily good timing on a repeat basis.”

Second, I find that there is no market-wide information leakage a priori, and private information is revealed through the trading process between informed institutional investors and uninformed investors.<sup>5</sup> More interestingly, I find that target firms that are bought and sold by institutional investors do not show any significant price run-ups before takeover bids, which implies that there is no market-wide information leakage prior to announcements – therefore there is no rumor which will lead to a run-up as some uninformed traders start speculating on the possibility of an M&A. Most of those uninformed traders end up losing money since many M&A

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<sup>5</sup> According to Grossman and Stiglitz (1976) and Kyle (1985), in a market with informed traders, private information is revealed through a trading process in which uninformed traders learn the information signal by updating their posterior beliefs on the underlying price after each trade. At the point of equilibrium, price is fully or partially revealed. If the information becomes market-wide at any point, price will jump immediately to a level that fully reveals the information.

rumors turn out to be incorrect.<sup>6</sup> One possible explanation for this is that institutional investors, although informed early, have more constraints and do not trade aggressively to induce possible price impacts. In fact I find that abnormal trading imbalances only account for 0.5% to 2% of the average daily trading volume. An alternative explanation is that institutions are better able to hide their trades, e.g., through algorithmic trading or breaking large trades into smaller ones that will not impact prices.

Third, although institutional investors are not a homogeneous group in terms of trading strategies, regulations, and information venues, I find, surprisingly, that they show very similar trading patterns around an event, with the exception of brokerage firms. All institutions have net buying imbalances before an announcement, and all but brokerage firms immediately sell their shares on and after an announcement day. Brokerage firms tend to be merger arbitrageurs in that they continue to buy more target firm stocks to speculate on final deal consummation. Merger arbitrageurs provide liquidity to the market at a price lower than the announced takeover price, therefore bearing the risk of failure by speculating on deal consummation. If the deal turns out to be successful, merger arbitrageurs sell these shares at their full premium price to the acquirers.

Fourth, the hypothesis of superior models is rejected in favor of inside information. Following the acquisition probability theory of Song and Walking (2000), I construct a prediction model to forecast future takeover targets such as rival

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<sup>6</sup> Gao and Oler (2007) show that buying on rumor target firms will actually lose money.

firms and examine institutional trading flow on these forecasted targets before M&A announcement. The trading pattern shows that they are selling these rival firms but only buying actual target firms over a 50 to 60 days period ahead, which indicates that institutional investors have a better information venue to anticipate the firms that actually become targets later, rather than use models to speculate on possible takeovers. Further, I find the quarterly holding position changes of some institutional investors have explanatory power in the prediction of the likelihood of future M&A deals. These institutions are serial leaders who can consistently identify actual target firms and start to accumulate shares as far as four to five quarters ahead, a pattern that is consistent with their behavior in the short-term window with daily data. These serial leaders are mostly brokerage firms, mutual fund and banks, whose positions and profits are much larger in magnitude than non-serial leader institutions. After the announcements, brokerage firms continue to hold or buy more of the shares for one or two quarters until final deal consummation, consistent with my conjecture in high frequency data that they act as merger arbitrageurs.

Finally, using the probability of informed trading (PIN) as a proxy to measure a cross-sectional degree of information asymmetry, I find that contemporaneously, the significant front-running pattern of institutional investors is associated with a high probability of informed trading, as they both use trading imbalances to proximate trading on private information. Moreover, when I sort target firms by previous year's PIN, I find that firms in general are characterized by different degree of information asymmetry exhibit similar patterns of systematic front-running patterns of institutions.

This paper is organized as follows. Section 1.2 briefly reviews related



literature. Section 1.3 describes data and methodology. Section 1.4 discusses results. Section 1.5 concludes and suggests directions for further research.

## **1.2 Literature Review**

The 2007 Institutional Investment Report, published annually by the United States Global Corporate Governance Research Center, shows that US institutional assets have risen to \$24.1 trillion in 2005 from \$7.6 trillion in 1990 and \$19.7 trillion in 2000. In 2005, institutional holdings accounted for 61.2 percent of the US equity market and 67.9 percent of the ownership of the largest 1,000 U.S. firms. With such a large stake at hand, the trading behavior of institutional investors has been of extreme interest to academics in recent years. This is a question that can only be answered through empirical investigation, though there is very limited public data available.

Empirical studies on institutional investors have focused on two aspects - their preference for choosing stocks cross-sectionally, and their trading behavior either over long- or short-term corporate events. The first aspect has been studied extensively. For example, Gompers and Metrick (2001) show that institutional investors prefer large and liquid stocks that have low past returns. Grinstein and Michaely (2005) show that institutions do not like firms that increase dividend payout, but prefer firms that increase share repurchase. Kumar (2005) finds that institutions exhibit an aversion for idiosyncratic skewness but prefer systematic skewness.

Investigation of the institutional investors' trading behavior around events is quite limited by the low frequency of publicly available data in the US equity market.

Most studies use the institutional ownership report that is filed with the U.S. Securities and Exchange Commission for end-of-quarter stock holdings. Using this quarterly data, Gibson, Safieddine and Sonti (2004) study the relationship between changes in institutional investment and returns of seasonal-equity-offering firms at the time of issuance. Yan and Zhang (2006) shows that short-term institutional investors are better informed. Burch and Swaminathan (2002) examine the trading behavior of institutions in response to earnings news. Dennis and Weston (2001) study the relationship between institutional ownership changes and the probability of informed trading. Field (1995) concludes that IPO firms with higher institutional investment perform well in the three-year period after the IPO. Bushee and Goodman (2007) investigate whether institutions trade based on private information about earnings news and returns. However, some results of these studies might fail to capture any intra-quarter covariance between institutional flow and corporate news release due to the low frequency of quarterly data.

Some recent papers have used proprietary datasets that provide high-frequency institutional trading flows. Kaniel, Liu, Saar, and Titman (2008) construct a unique dataset using the NYSE's Consolidated Equity Audit Trail Data (CAUD) file, which contains a field called Account Type that specifies the origination of each order – an institution or an individual. They study the trading of individuals and institutions around earnings announcements and find that institutions are news-momentum traders. Griffin, Harris, and Topaloglu (2003) investigate the trades of NASDAQ 100 firms with a special classification field of individuals, institutions, and market-makers. They find a strong positive relation between institutional trading and short-term past stock returns, both daily and intraday. Froot, O'Connell, and Seasholes (2001), Froot and

Teo (2007), and O’Connell and Teo (2007) use custodial data from State Street Corporation to study daily institutional trading behavior. They find that institutional flows are positively related to future stock returns, and institutions take on more risk following an increase in net profit and loss. These studies are difficult to replicate, and their samples are restricted by both time period and the coverage of institutional investors.

Another group of papers attempts to use publicly available data from the NYSE Trades and Quotes (TAQ) to examine institutional trading behavior at a high frequency level. Lee and Radhakrishna (2000) suggest a separating rule by dollar trading size above or below certain threshold values to distinguish order flows of institutional investors from those of individual investors. They find that a \$20,000 cutoff most effectively classifies institutional trades in small stocks. Shanthikumar (2004) uses their method to study institutional trading around earnings announcements, and finds evidence that large traders react strongly to an earnings surprise and capitalize on earnings announcement drift. However, Campbell, Ramadorai, and Schwartz (2008) find that the Lee-Radhakrishna approach of defining institutional trading works poorly when benchmarked against the quarterly report of institutional ownership positions in 13F.

To study the dynamics of daily institutional trading behavior using non-proprietary data, Campbell, Ramadorai, and Schwartz (2008) develop a methodology to infer the daily trading flows of institutional investors based on the publicly available high frequency NYSE Trades and Quotes (TAQ) data and the quarterly changes in institutional ownership positions on the 13F report. They show that their

methodology is better than simple cutoff rules since inferred daily institutional trading flows are more consistent with reported quarterly institutional ownership changes. This paper follows Campbell-Ramadorai-Schwartz methodology (CRS thereafter) with some modifications to incorporate different trading strategies from different fiduciary types of institutional investors.

Literature on high-frequency institutional trading behavior around corporate events focuses on exploring the post-earnings-announcement-drift (PEAD) phenomenon. Campbell, Ramadorai, and Schwartz (2008) examine whether daily institutional investor trading contributes to PEAD and find that institutional investors generate short-term loss in demand for liquidity, but that they anticipate earnings surprises and PEAD to make longer-term profits. Kaniel, Liu, Saar, and Titman (2007) study institutional and individual trading behavior and PEAD. Using a unique dataset from NYSE, they find that institutions sell stocks with higher earnings uncertainty, and trade for liquidity reasons, and that the contrarian trading behavior of individuals after a news announcement may contribute to PEAD. Rosa, To, and Walter (2007) examine UK fund managers' daily trading behavior around M&A announcements and find that they trade principally on perceived good news. Ashraf and Jayaraman (2007) study institutional investors' holding and trading behavior in acquiring firm stocks in response to M&A announcements. However, their use of the quarterly 13F report does not show whether institutions are reacting to corporate news a few days before and after M&A announcements to exploit huge price premiums. The short length of an event window is important since it is critical to determining whether they obtain an informational advantage for these firms. Griffin, Shu, and Topaloglu (2007) examine institutional investors' trading before takeover events for NASDAQ-

listed target firms and find that institutional investors are small net sellers, and that their trading cannot predict takeover premiums. Hasbrouck (1991a,b) uses a VAR decomposition to show that there is a permanent price impact of information-driven trading ahead of an M&A announcement. Huang and Walkling (1987), using a simple market model to compute abnormal returns, find that average abnormal returns for target firms in their sample of 1977 to 1982 are positive starting from 50 days ahead.

Do institutional investors possess a comparative informational advantage in anticipating M&A events and trade in advance to exploit large price premiums on target firms that they own? Is there heterogeneity among institutional investors with respect to skills, trading strategies, and information? This paper fills the gap in the literature.

### **1.3 Data and Methodology**

#### **1.3.1 Data**

Four data sources are used in this study: the NYSE Trade and Quote (TAQ), the Thomson Financial Institutional Ownership report (13F), CRSP, and the SDC/Spectrum Merger and Acquisition database from Jan 1, 1993 to Dec 31, 2004.

I start my sample from 1993, when the NYSE TAQ data becomes available. I include all common stocks of target firms that are traded on the NYSE or AMEX<sup>7</sup>, and

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<sup>7</sup> Ellis, Michaely and O'Hara (2000) show that in NASDAQ, the use of trade classification rules such as those in Lee and Ready (2000), introduce biases in classifying large trades and trades initiated during a high volume period, which is the case that I investigate here. Therefore, I do not include the NASDAQ stocks in my sample.

exclude all close-end funds, American Depositary Receipts (ADRs) and Real Estate Investment Trusts (REITs). My final sample contains 1,638 target firms.

The NYSE TAQ data includes all trades and quotes during normal trading hours on common stocks and excludes all close-end funds, ADRs, and REITs. To classify the direction of a transaction, Lee and Ready (1991) develop an algorithm that compares transaction price to posted bid and ask quotes. If the price of a trade is higher (lower) than the mid-point of the contemporaneous bid-ask quote, the trade is classified as a buy (sell). If they are equal, the algorithm classifies trades on an up-tick as buys, and those on a downtick as sells. All zero-tick trades that cannot be identified as buy or sell, plus the cancelled trades or batched or split-up trades that cannot be classified by the Lee-Ready algorithm are put into a separate bin of unclassifiable trades. For details on the Lee and Ready (1991) algorithm, see Appendix A.

Institutional investment managers who exercise investment discretion of \$100 million or more must report to the SEC their end-of-quarter stock holdings on Form 13F. In general, an institutional investment manager is: (1) an entity that invests in, or buys and sells, securities for its own account; or (2) a person or an entity that exercises investment discretion over the account of any other person or entity. Thomson Financial distributes a digital database of institutional quarterly 13F filings, and decomposes institutional ownership structures into five groups: (1) banks, (2) insurance companies, (3) investment companies (mutual funds), (4) investment advisors (major brokerage firms), (5) others, including pension funds and university endowments. This categorization is not always precise; for example, if a brokerage firm has a mutual fund subsidiary that makes up over 50 percent of total 13F assets

under management, then this firm falls into category (3) (Gompers and Metrick (2001)).<sup>8</sup> The quarterly frequency of this dataset is the major drawback for any short-window event studies. To remedy this issue, I follow procedures developed by Campbell, Ramadorai, and Schwartz (2008) with some modifications to infer daily trading flows from each type of institution, combining their quarterly holding changes with NYSE TAQ data.

CRSP daily files provide the daily common stock share price, number of shares outstanding, exchange codes, stock returns, value-weighted, and equal-weighted market returns, etc. I use CRSP PERMNO to match CRSP data to TAQ and 13F stocks that are traded on the NYSE and AMEX.

The Merger and Acquisition data is from the Securities Data Corporation (SDC) database provided by Thomson Financial. My sample covers merger announcements for US public firms from Jan 1, 1993 to Dec 31, 2004, excluding all closed-end funds, ADRs, and REITs. To be consistent with my institutional trading data, I choose US target firms that are only trading on the NYSE or AMEX, and, particularly, firms that were owned by institutional investors before events.

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<sup>8</sup> According to Thomson Financial Data Specifications, during the integration with the former Technimetrics, the institutional classification mapping was changed and merged with the mapping from Technimetrics. This resulted in a mapping error. Consequently, numerous institutions added to the "Type 5" category that should not have been since year 1999. Moreover, between the end of 1998 and the first quarter of 1999, there are errors where Type 2 codes were indexed as Type 5 ("All Others"). Neither problem has been corrected and unfortunately they will not be corrected in the feed files, according to Thomson Financials. At this moment we cannot get a better classification than what Thomson Financial has to offer; therefore there will be lots of noise in Type 5 institutional ownership holdings after year 1999.

### 1.3.2 Abnormal Returns

Following literature standards, I use two methods to compute abnormal returns, and they give qualitatively the same results<sup>9</sup>.

First, the abnormal return of stock  $i$  over the event window is defined as the difference between the daily stock return and the CRSP value-weighted market index return:

$$AR_{it} = r_{it} - r_{mt} \quad (1)$$

Where  $r_i$  is the return on firm  $i$  on day  $t$  and  $r_m$  is the CRSP value-weighted market index return.

Second, I use a simple market model to estimate expected stock returns as the benchmark returns over the non-announcement period  $[-250, -31]$ , and compute abnormal returns during the event window  $[-30, +30]$ :

$$R_{it} = \alpha_i + \beta_i \cdot R_{mt} + \varepsilon_{it} \quad (2)$$

Where  $t$  is from day -250 to day -31. The abnormal return for stock  $i$  is then defined as:

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<sup>9</sup> For short-window event studies, daily returns are relatively small so that results will not significantly improve by using market and risk adjusted models. Robustness test using market and risk adjusted models show that the results are qualitatively the same.



$$AR_{it} = R_{it} - E(R_{it}) \quad (3)$$

Where  $E(R_{it})$  is the expected returns for stock  $i$  that are estimated from equation (2),  $t$  is from day -30 to day +30. The cumulative abnormal return (CAR) from time  $t_1$  to  $t_2$  (i.e., horizon length  $L = t_2 - t_1 + 1$ ) is defined as:

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_t \quad (4)$$

A standard test statistic is the CAR divided by an estimate of its standard deviation. There are alternative ways to estimate this standard deviation in the literature<sup>10</sup>

(Campbell, Lo, and MacKinlay, 1997). The test statistic is given by:

$$T = \frac{CAR(t_1, t_2)}{\sqrt{L} * SE(AR_t)} \quad (5)$$

### 1.3.3 Daily Abnormal Trading

Institutional investors report their equity holding positions to the SEC at each quarter-end on form 13F, so past studies have relied on this quarterly data to measure institutional trading. However, the low frequency of this dataset does not capture anything within quarters, especially when there are significant events happening within several days. Other studies have used proprietary data<sup>11</sup>. To get a better

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<sup>10</sup> Brown and Warner (1980, 1985) have shown that, in short-horizon event studies, an alternative test using standardized abnormal returns (first estimate the standard deviation of abnormal returns using time-series return data for each firm, then divide each estimated abnormal return with the standard deviation) makes little difference with the simple test statistic here.

<sup>11</sup> For example, Kaniel, Liu, Saar, and Titman (2007), Griffin, Harris, and Topaloglu (2003), Froot, O'Connell, and Seasholes (2001), Froot and Teo (2007), and O'Connell and Teo (2007).

understanding of institutional trading behavior using publicly available data, I combine the 13F quarterly data with high frequency NYSE TAQ data to infer the daily equity holding positions of institutional investors. I follow a regression methodology developed by Campbell, Ramadorai, and Schwartz (2008) (CRS thereafter). I apply some modifications to incorporate the investment strategies of different fiduciary types of institutional investors. The CRS methodology is better than simple cutoff rules in two ways: first, it does not suffer any selection bias or restrictions by using high-frequency proprietary database; second, the daily institutional trading flows are more consistent with the reported quarterly institutional ownership changes.

To implement the CRS methodology, I collect the NYSE TAQ intraday data from 1993 to 2004 and use the Lee-Ready algorithm to classify the direction of each trade – buy, sell or unclassified. Next, I categorize each buy/sell/unclassified transaction by dollar size into 19 bins with lower cutoffs: \$0, \$2000, \$3000, \$5000, \$7000, \$9000, \$10,000, \$20,000, \$30,000, \$50,000, \$70,000, \$90,000, \$100,000, \$200,000, \$300,000, \$500,000, \$700,000, \$900,000, and \$1 million. Third, I aggregate all shares traded in each buy/sell/unclassified bin to daily frequency, and normalize each daily bin by the daily shares outstanding as reported in CRSP. Finally, I aggregate normalized daily buy/sell/unclassified volume to the quarterly frequency.<sup>12</sup>

The change in the quarterly level of institutional ownership for a stock can be explained by a regression on past changes and levels of institutional shares for the stock, and the buy/sell/ unclassifiable volume in all 19 trade-size bins during the quarter, restricting the coefficient on buy and sell volume to be equal and opposite:

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<sup>12</sup> For complete details, refer to Appendix B.

$$\Delta Y_{i,t} = \alpha + \phi Y_{i,t-1} + \rho \Delta Y_{i,t-1} + \beta_U U_{i,t} + \sum_z \beta_{FZ} F_{Zi,t} + \varepsilon_{i,t} \quad (6)$$

Where,  $Y_{i,t}$  is the share of firm  $i$  that is owned by institutions at the end of quarter  $t$ ,  $\Delta Y_{i,t}$  is the change of institutional ownership between quarter  $t$  and  $t-1$ ,  $U_{i,t}$  is unclassifiable total trading volume,  $B_{i,t}$  is total buy volume,  $S_{i,t}$  is total sell volume in stock  $i$  during quarter  $t$  (all variables are expressed as percentages of the end-of-quarter  $t$  shares outstanding of stock  $i$ ),  $F_{i,t} = B_{i,t} - S_{i,t}$ , and  $Z$  indexes trade size bins. Table I shows the regression results.

To reduce the number of coefficients to be estimated yet still be able to capture the shape suggested by the unrestricted specifications, I use the Nelson and Siegel (1987) exponential smoothing function, following the CRS paper. This method requires estimating a function  $\beta(Z, v_{it})$  that varies with trade size  $Z$  and an interaction variable  $v_{it}$ , and is of the form:

$$\beta(Z, v_{i,t}) = b_{01} + b_{02}v_{i,t} + (b_{11} + b_{12}v_{i,t} + b_{21} + b_{22}v_{i,t})[1 - e^{-Z/\tau}] \frac{\tau}{Z} - (b_{21} + b_{22}v_{i,t})e^{-Z/\tau} \quad (7)$$

Defining  $g_1(Z) = [1 - e^{-Z/\tau}] \frac{\tau}{Z}$  and  $g_2(Z) = [1 - e^{-Z/\tau}] \frac{\tau}{Z} - e^{-Z/\tau}$ , I estimate the function using nonlinear least squares, searching over different values of  $\tau$ , to select the function that maximizes the  $R^2$  statistics:

$$\begin{aligned} \Delta Y_{i,t} = & \alpha_{i,t} + \phi Y_{i,t-1} + \rho \Delta Y_{i,t-1} + \beta_U U_{i,t} + \beta_{v_i}(v_{i,t-1} U_{i,t}) + b_{01} \sum_z F_{z,i,t} + b_{02} \sum_z v_{i,t-1} F_{z,i,t} \\ & + b_{11} \sum_z g_1(Z) F_{z,i,t} + b_{12} \sum_z g_1(Z) v_{i,t-1} F_{z,i,t} + b_{21} \sum_z g_2(Z) F_{z,i,t} + b_{22} \sum_z g_2(Z) v_{i,t-1} F_{z,i,t} + \varepsilon_{i,t} \end{aligned} \quad (8)$$

I estimate the equation separately for each quintile of market capitalization using the level of lagged institutional ownership ( $Y_{i,t-1}$ ) as interaction variable  $v$ . The standard errors are robust in presence of heteroscedasticity (White's correction), autocorrelation (Newey-West), and cross-sectional correlation, following procedures suggested in Petersen (2007). Clustering by firms, clustering by time, and adjusted Fama-MacBeth method all give similar results<sup>13</sup>.

Following CRS, I construct the daily institutional flows in a similar equation:

$$\begin{aligned} \Delta Y_{i,d} = & \alpha d + \phi \Delta Y_{i,t-1} + \rho d \Delta Y_{i,t-1} + \beta u U_{i,d} + \beta v (Y_{i,t-1} U_{i,d}) \\ & + b_{01} \sum_z F_{z,i,d} + b_{02} \sum_z Y_{i,t-1} F_{z,i,d} + b_{11} \sum_z g_1(Z) F_{z,i,d} \\ & + b_{12} \sum_z g_1(Z) Y_{i,t-1} F_{z,i,d} + b_{21} \sum_z g_2(Z) F_{z,i,d} + b_{22} \sum_z g_2(Z) Y_{i,t-1} F_{z,i,d} + \varepsilon_{i,d} \end{aligned} \quad (9)$$

The assumption for aggregating daily institutional flow equation (9) up to the quarterly frequency equation (8) is that “the error in measured daily institutional ownership  $\varepsilon_{id}$  is uncorrelated at all leads and lags within a quarter with all of the right hand side variables in equation (9). This exogeneity assumption guarantees that the parameters of the daily function  $b_{01}$ ,  $b_{02}$ ,  $b_{11}$ ,  $b_{12}$ ,  $b_{21}$ ,  $b_{22}$  and  $\tau$  (parameter in  $g_1(Z)$  and  $g_2(Z)$ ) be the same as those estimated at the quarterly frequency.”<sup>14</sup> From equation (8) I estimate the parameters and recover the parameters of equation (9), then finally

<sup>13</sup> When regressing changes of quarterly ownership on buy/sell/unclassified volume, I include lags of ownership, and try clustering by quarters and clustering by firms. The results are qualitatively the same.

<sup>14</sup> Campbell, Ramadorai and Schwartz (2008).

construct the predicted value  $E_d[\Delta Y_{id}]$  for each stock  $i$  for each day  $d$ , as a percentage of CRSP daily shares outstanding. I multiply this by the CRSP daily shares outstanding to get my institutional daily flow measure – Daily Net Buying Dollar Imbalance. To avoid ad-hoc assumptions, the quarterly parameters ( $\rho$ ,  $\phi$ ,  $\alpha$  and  $\varepsilon$ ) are not incorporated into the daily level, so the values of these parameters are set to zero at daily level. I repeat the same procedures for different institutional types and different firm sizes.

I construct the daily abnormal institutional trading flows by an imbalance measure in excess of a benchmark. I define the institutional daily trading imbalance measure  $IMB_{i,t}$  as the daily net buy (buy – sell) dollar volume normalized by average daily dollar volume in calendar year  $t$ . The institutional abnormal daily trading imbalance  $ABIMB_{i,t}$  is the daily trading imbalance in excess of the average daily trading imbalance over the entire sample period.<sup>15</sup>

$$IMB_{i,t} = \frac{\text{Daily Net Buying Dollar Volume}_{i,t}}{\text{Average Daily Dollar Volume over Year } t}$$

$$ABIMB_{i,t} = IMB_{i,t} - \frac{1}{T} \sum_{\text{all days in sample period}} IMB_{i,t} \quad (10)$$

Alternatively, I use another common practice in the literature:

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<sup>15</sup> There is an increasing trend in daily trading imbalance over the long term, since institutions have increased their shares of stocks over time, as shown by Gompers and Metrick (2001). But subtracting

$$\begin{aligned}
\text{IMB}_{i,t} &= \frac{\text{Daily Net Buying Imbalances}_{i,t}}{\text{CRSP Daily Shares Outstanding}_t} \\
\text{ABIMB}_{i,t} &= (\text{IMB}_{i,t} - \frac{1}{T} \sum_{\text{all days in sample period}} \text{IMB}_{i,t}) * \text{CRSP Daily Shares Outstanding}
\end{aligned} \tag{11}$$

Where, the institutional daily imbalance of stock *i* is defined as the daily net buying imbalances divided by the CRSP daily shares outstanding of stock *i* at day *t*. The abnormal daily imbalance of stock *i* is defined as the difference between the daily imbalance and the average daily imbalance over entire sample period, then multiply by the CRSP daily shares outstanding.

I construct similar measures of daily abnormal trading imbalances for five quartiles of market capitalization, and for each type of institutional investors: (1) banks, (2) insurance companies, (3) investment companies (mutual funds), (4) investment advisors (major brokerage firms), (5) others, including pension funds and university endowments.

#### **1.3.4 Is It Inside Information or Better Model?**

As sophisticated investors, institutions can easily argue that their models work better in predicting future M&A deals, not that they obtain inside information. Following the acquisition probability hypothesis of Song and Walking (2000), I construct a prediction model of possible takeover targets and examine the trading flow of

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the mean of a trending variable does not affect my results. I also subtract the time trend for robustness and it does not affect my results, either.

institutional investors on these firms<sup>16</sup>. The predicted takeover targets consist of rival firms in the same industry (four-digit SIC code) once the first M&A deal is announced after a dormant period of 13 months. If institutional investors accumulate shares in these rival firms with same pattern as in the actual targets, it indicates that they do not have inside information but only superior models to speculate on future targets. On the other hand, if the institutional investors trading patterns are indeed different, it indicates that they are more likely to have inside information.

If the institutional investors do have inside information on the actual future targets, their trading positions will have prediction power on the likelihood of future M&A announcements. If an institution happens to know a firm becomes a target by random lottery or by assigning equal probabilities to the firms they own, it is not inside information. If an institution can consistently predict the future M&A deals and accumulate holding positions in these targets several quarters ahead with a surprisingly good timing on a repeat basis, this institution is a serial leader who is more likely to trade on inside information. To test this latter hypothesis, I use a Logit model to predict the likelihood of future M&A deals by using the previous quarterly holding position changes by these serial leaders. If their quarterly holding position changes have explanatory power in predicting the probability of future M&A announcements in the Logit model, then these serial leaders possess inside information on the actual targets.

The Logit model is defined in equation (12):

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<sup>16</sup> This model has been widely cited to predict takeover targets in M&A literature in academia. There might be better models available in the industry, which I am not aware of.

$$P_i = \frac{1}{1 + \exp(-(\alpha_i + \sum_{j=0}^4 \beta_{ij} * (Y_{i,t-j} - Y_{i,t-j-1}) + \varepsilon_i))} \quad (12)$$

Where,  $P_i$  is the probability of an M&A announcement in quarter  $t$  for a target firm  $i$ .  $P_i$  is 1 if there is an announcement in quarter  $t$ ; 0 otherwise.  $Y_{i,t-j} - Y_{i,t-j-1}$  is the quarterly change of holding positions on the target firm stocks by a certain institution from quarter  $(t-j-1)$  to quarter  $(t-j)$ , and  $\varepsilon_i$  is the error term.

I estimate the logit model for each institutional investor on their quarterly holding positions across all target firms they hold in the M&A database. I use this model to identify serial leaders – the institutional investors who can consistently forecast the future M&A announcement and therefore accumulate target firm shares on a repeat basis. Then I compute the profit of the serial leaders over quarter  $[-6,0]$  and compare with the profit of the non-serial leaders. For model robustness, I separate the data into two periods: in-sample period for years before 2000 and out-of-sample period for years after 2000, and test whether the logit model with in-sample holding position changes by the serial leaders can better predict the likelihood of the out-of-sample actual M&A deals than a naïve model which assigns equal probabilities to the future target firms.

### 1.3.5 Probability of Informed Trading (PIN)

Market microstructure literature views the trading process as a sequential game where insiders' private information is revealed to noise traders and market makers as they



update their posterior beliefs upon observed order flows. Easley, Kiefer and O'Hara (1997) develop a framework to extract and analyze information from the trading process. Following their model, Easley, Hvidkjaer, and O'Hara (2004) find that stocks with higher probability of informed trading, defined as the PIN measure, have a higher excess return, controlling for the Fama-French factors. Other empirical studies have shown that the PIN measure is highly correlated with stock return variations, the bid-ask spread, and the cost of capital (Durnev et al (2004), Chuang and Li (2003), Botosan and Plumlee (2003)).

In a market with institutional investors, some institutions, such as brokerage firms, are able to observe the submitted orders of their clients and update their beliefs accordingly. Other institutional investors may simply have a better information venue or better research skills to predict the possible takeover targets. As a proxy to measure the degree of information asymmetry in stock trading, higher PIN implies that a firm has higher probability of buying and selling orders submitted by informed traders.

Since PIN is estimated based on observed daily order imbalances in the market, it is plausible that target firms that are in general characterized by different degree of information asymmetry – high PIN – will exhibit similar patterns of systematic front-running patterns of institutional trading. It is also possible that the amount of informed trading will increase mainly due to informed trading by institutional investors before the M&A announcement. To distinguish the contemporaneous effect with prediction effect, I test two hypotheses:

*Hypothesis 1 Null:* Institutional trading is in fact informed trading

*Hypothesis 1 Alternative:* Institutional trading is not informed trading

*Hypothesis 2 Null:* Stocks that in general are characterized by different degree of information asymmetry exhibit similar patterns of systematic front-running patterns of institutions

*Hypothesis 2 Alternative:* Stocks that in general are characterized by different degree of information asymmetry exhibit different patterns of systematic front-running patterns of institutions.

I test the first hypothesis by sorting contemporaneous PIN<sup>17</sup> into 10 deciles and examine the difference in institutional trading pattern around the event for target firms with high PIN. I test the second hypothesis by sorting on lagged one-year PIN into 10 deciles and examine whether target firms with high PIN will more likely to incur systematic front-running behavior by institutional investors during the event year.

## **1.4 Results**

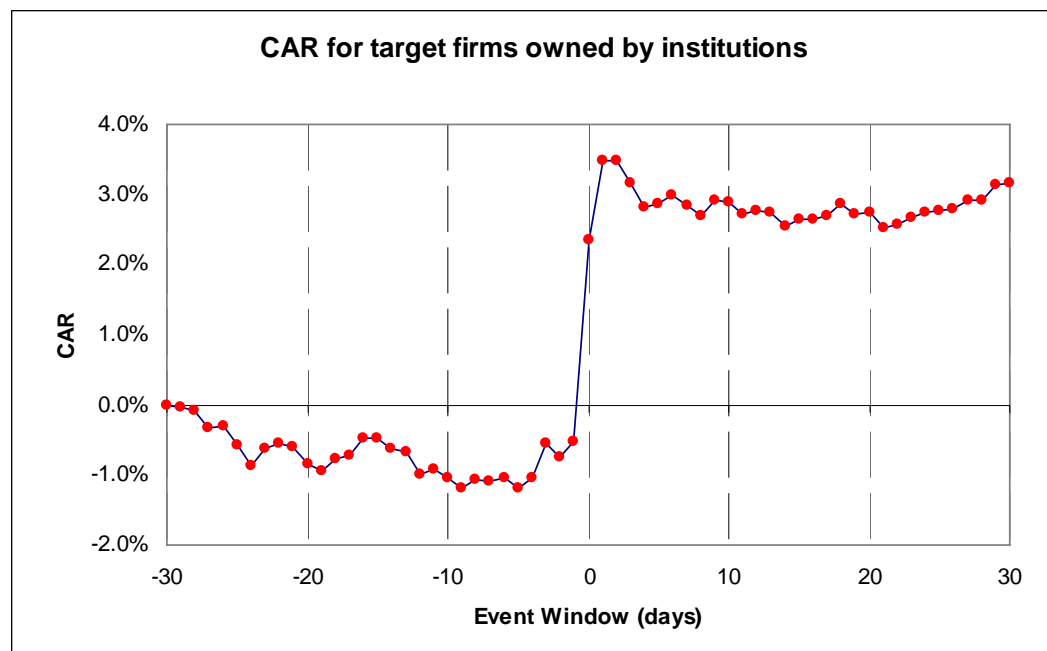
### **1.4.1 Abnormal Returns**

Figure 1.1 shows the cumulative abnormal returns for target firms that are traded by institutional investors on NYSE and AMEX. Interestingly, for target firms that are

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<sup>17</sup> The annual PIN estimates are obtained from Soeren Hvidkjaer's website.

owned, bought, and sold by institutional investors, there is no significant price run-up over 30 or 20 or 10 days ahead of an event day<sup>18</sup>. The random abnormal return pattern of target firms before the announcement implies that there is no wide-spread information leakage in the market prior to the M&A announcement – otherwise we should observe an immediate price jump to the acquiring price level.



**Figure 1.1** CAR for target firms that are bought and sold by institutional investors on NYSE and AMEX over [-30,+30]

Given this observed CAR pattern with no significant run-ups, an uninformed investor with no prior information will not buy a significant quantity of target firm stocks days or weeks before information becomes public. Therefore any pre-

<sup>18</sup> When I plot all target firms trading on NYSE and AMEX, including those that are not traded by institutions, there exists a price run-up of about 6% in 20 days prior to announcements.

announcement significant buying orders of a target firm are suspect of trading on inside information. In the next section I investigate the trading behavior of institutional investors before and after deal announcements.

If institutions are trading with significant net buying patterns, why the target firms do not show price run-ups? Griffin, Shu, and Topgaloglu's (2007) show that individual trading is more likely to have a price impact on the target firms and their trading imbalances positively predict cumulative excess returns on the target firms. Institutions are more constrained in their trading strategies so that their trading volume could be small in magnitude prior to the event. This explanation is also consistent with my findings on the small magnitude of institutional trading abnormal imbalances, which only accounts for 0.5% to 2% of daily average trading volume prior to an event. Alternatively, the non-significant, even negative CAR of target firms owned by institutions suggests that institutions might be able to hide their trades more effectively, e.g., through algorithmic trading or breaking into smaller trades that will not impact prices<sup>19</sup>.

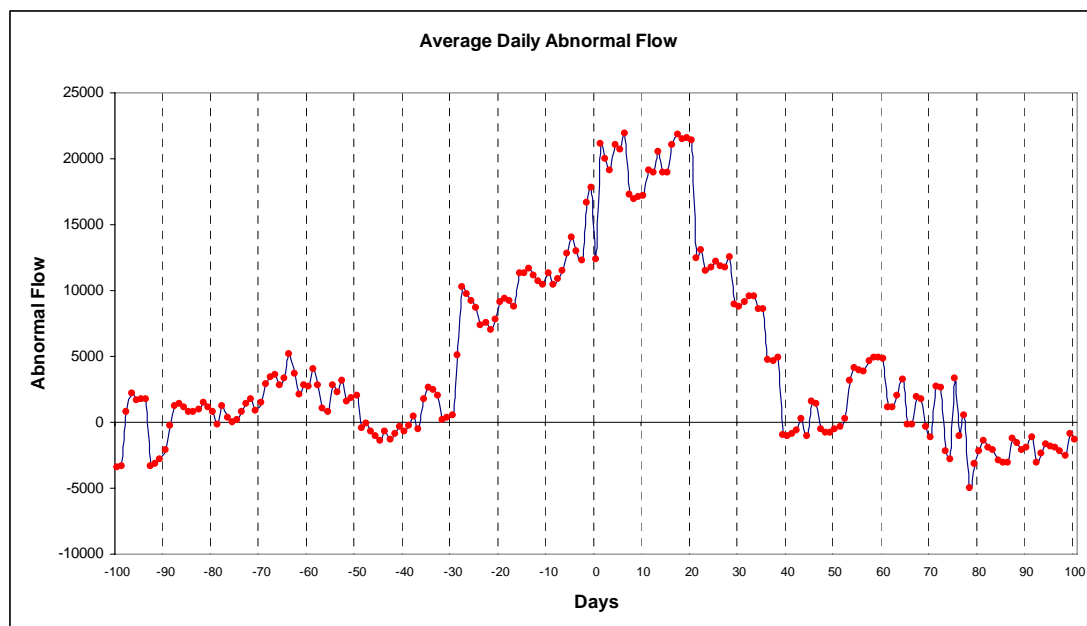
#### **1.4.2 Daily Abnormal Trading Flow**

Institutional abnormal trading behavior on target firms before and after M&A announcements reveals very interesting patterns. Figure 1.2 gives results. All institutional investors start to accumulate shares in target firms as far as 30 trading days ahead, with statistically significant buying positions starting around day (-16). The average institutional abnormal imbalances, as measured by the daily net buying in

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<sup>19</sup> The quarter-to-quarter shares change on average is 1000 shares.

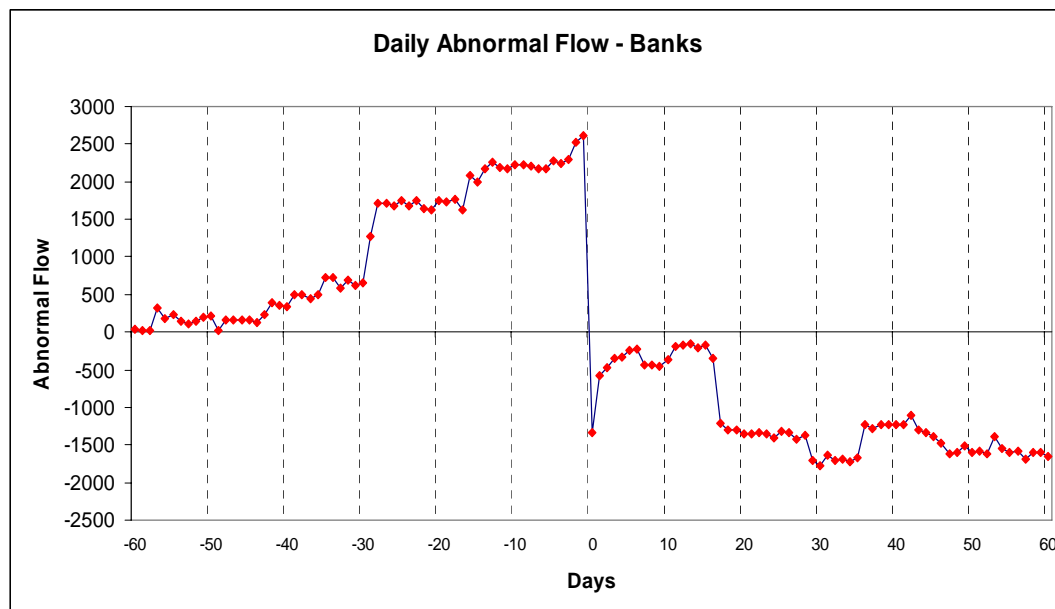
excess of one-year average net buying orders, have an inverted “U” shape over a [-30, +40] days window. Part of the shape after the initial public announcement date is possibly driven by the large buying orders of investment advisors, who act as merger arbitragers and begin to buy more target stocks from other institutions and individuals who are willing to sell right after the announcement. On the announcement day, most institutional investors (except investment advisors) immediately reverse their trading positions to capitalize on their prior information, a pattern that is consistent with the behavior of early informed investors as “short-term profit takers” described in a theoretical model by Hirshleifer, Subrahmanyam, and Titman (1994).



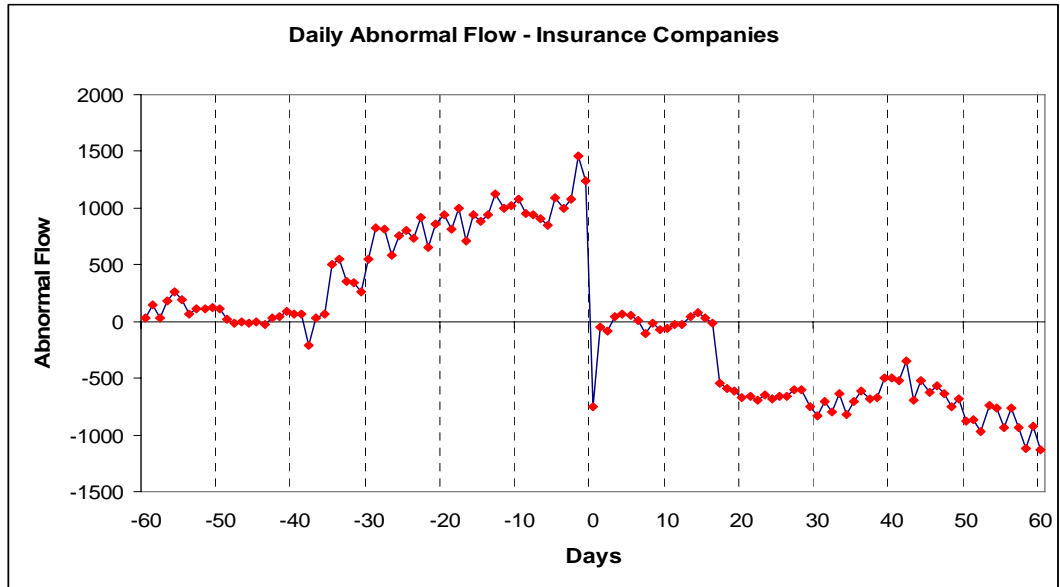
**Figure 1.2** Daily abnormal flows over M&A  
event window [-100, +100]

Figures 1.3a to 1.3d shows daily abnormal flows over an event window by

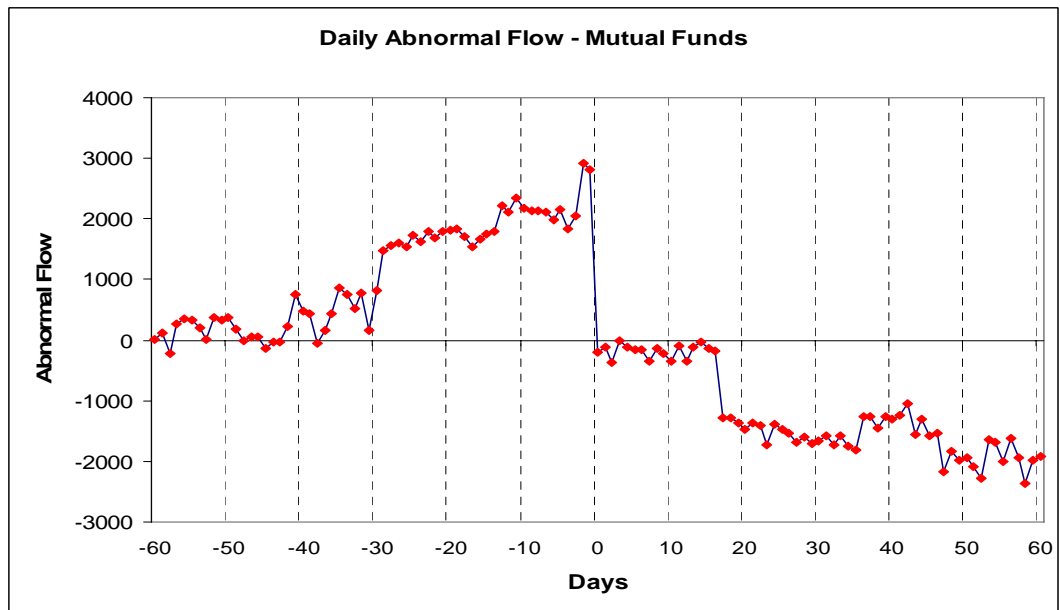
each type of institution. Although institutional investors are not a homogeneous group in terms of trading strategies, regulation rules, and information venues, I find that, surprisingly, they show very similar trading patterns around the event, with the exception of brokerage firms. Almost all institutions have abnormal buying orders starting 30 to 40 days prior to the announcement day. All institutions reverse their positions immediately on the announcement day, except for investment advisors, who tend to speculate on final deal consummation (merger arbitrage) in that they continue to buy more target firm stocks at the market price, which is lower than the acquirer offer price because of the uncertainty of deal success. If the deal turns out to be successful, merger arbitrageurs sell the shares at the full premium price to the acquirers.



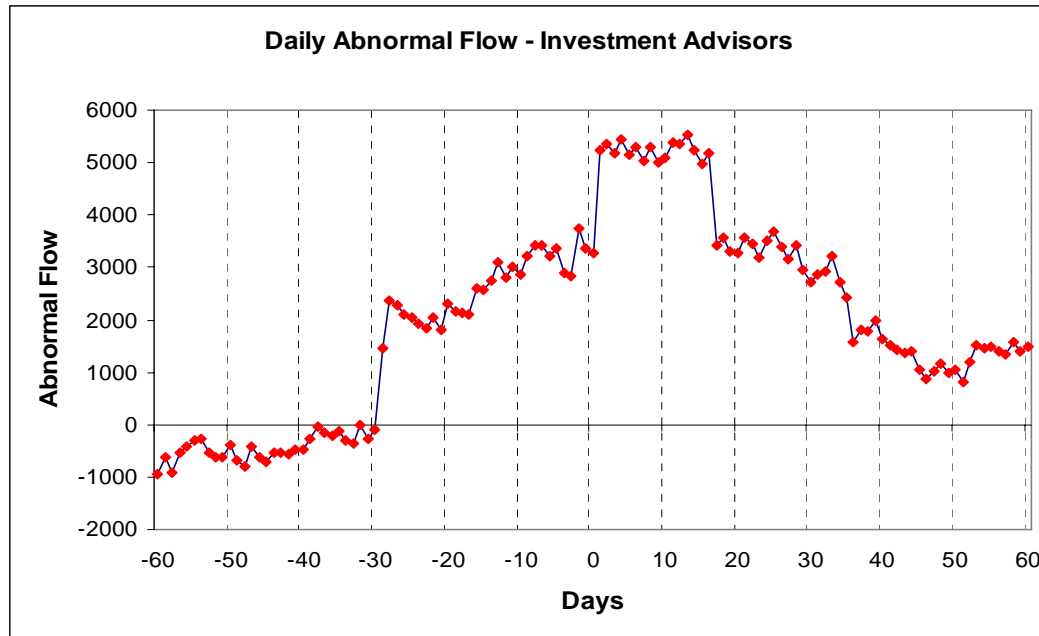
**Figure 1.3a** Daily abnormal flows over M&A event  
window [-60, +60] by Banks



**Figure 1.3b** Daily abnormal flows over M&A event  
window [-60, +60] by Insurance Companies



**Figure 1.3c** Daily abnormal flows over M&A event  
window [-60, +60] by Mutual Funds



**Figure 1.3d** Daily abnormal flows over M&A event  
window [-60, +60] by Investment Advisors

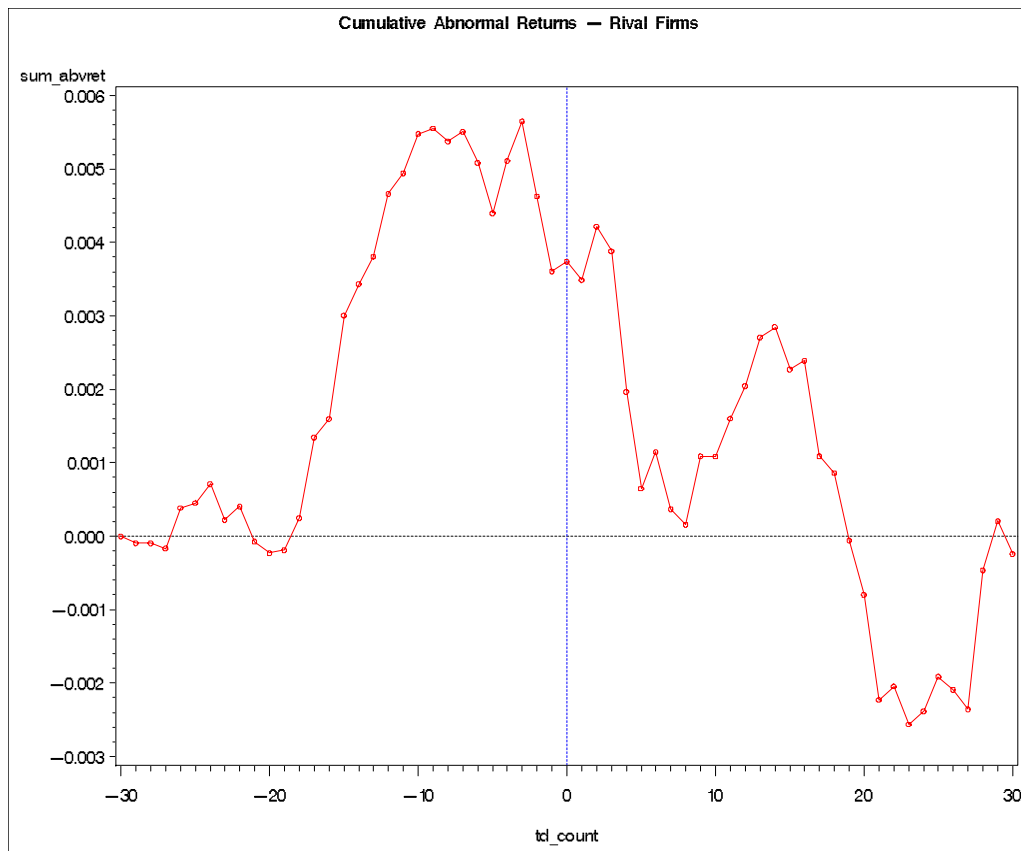
### 1.4.3 Is It Inside Information or Better Models?

One alternative interpretation is that institutional investors have superior models to predict future target firms. To test whether this interpretation is valid, I construct the possible rival firms of targets using the acquisition probability hypothesis test developed by Song and Walking (2000). The rival firm portfolio consists of rival firms in the same industry (four-digit SIC code) when the first M&A deal is announced after a dormant period of 13 months.

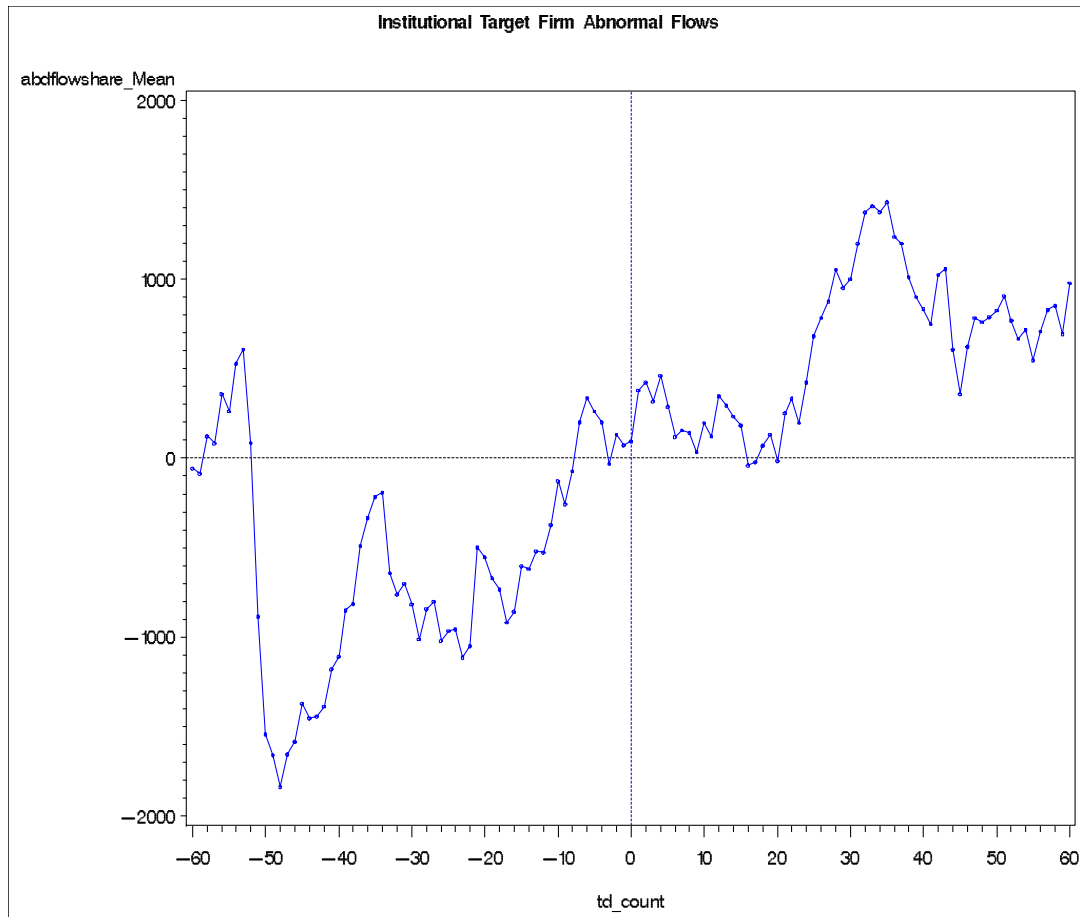
The abnormal returns of rival firms before and after the announcement are consistent with past empirical results – rival firms have a huge run-up in returns due to



market speculation before the announcement and soon revert back afterwards as the rumor dies out (Figure 1.4a). However, institutional investors show a significant pattern of selling the rival firm stocks before the announcement, as in Figure 1.4b. The institutional trading pattern on rival firms shows that institutional investors have a better information venue to anticipate the firms that actually become targets later, rather than to speculate on possible takeovers.



**Figure 1.4a** Cumulative Abnormal Returns for Predicted Target Firms by Acquisition Possibility Hypothesis



**Figure 1.4b** Institutional Trading on Predicted Target Firms

Are all institutional investors the same? Within each category of institutional investors, are there serial leaders? If some institutional investors have inside information on which firms will become targets in the future, they will accumulate holding positions in these firms several quarters ahead. If such behavior persists, these institutional investors are serial leaders who can consistently predict the future M&A targets by significantly increasing their holding positions before M&A

announcements. The results of logit model by each institutional investors show that there are such serial leaders whose quarterly position changes have positive effect on increasing the probability of a firm being actual M&A target<sup>20</sup>. Table 1.1 shows two examples of the logit model regression results from two serial leaders: a brokerage firm and a bank. The first one with a brokerage firm is jointly significant with a Chi-square value of 38.9 using likelihood ratio. The coefficient for quarterly holdings change from quarter (t-2) to (t-1) is significantly positive at 0.000023, which translates to increase the probability of future M&A announcement by 51% for every additional 1,000 shares this brokerage firm buys over that quarter. In the second example with a bank's holdings, the coefficient for quarterly holdings change from quarter (t-3) to (t-2) is significantly positive at 0.000318. Most serial leaders have similar coefficient estimates either from quarter (t-5) to (t-4), or from (t-4) to (t-3), or from (t-3) to (t-2). Consistent with my previous conjecture that brokerage firms are merger arbitragers and banks are not, the coefficients of quarterly holding changes from (t-1) to announcement quarter t show different signs for brokerage firms and banks. For brokerage firm, the coefficient is significantly positive, because brokerage firms are merger arbitragers so they still keep buying over the announcement quarter and afterwards (shown in Figure 1.5); while banks are short-term profit takers so the coefficient of quarterly holdings from quarter (t-1) to quarter t is significant but negative, because banks will unwind their positions immediately as the deal is announced. In results not showing here for brevity, the serial leaders are mostly brokerage firms, mutual funds and banks.

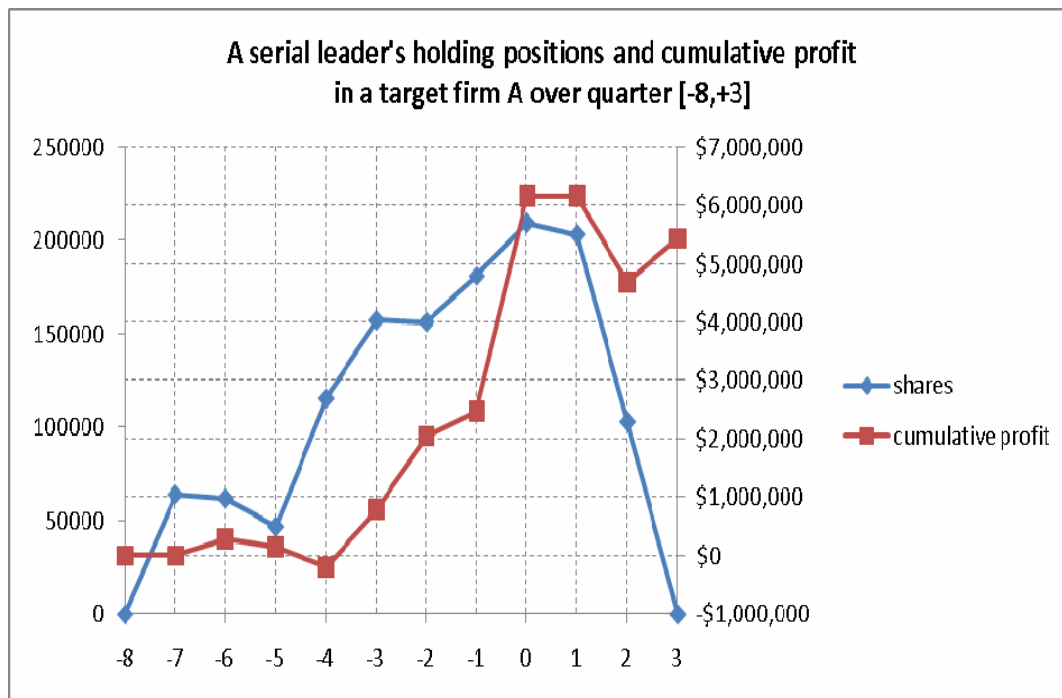
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<sup>20</sup> For robustness test, I separate the data into years before 2000 and out-of-sample period after 2000. An out-of-sample prediction shows that the logit model with serial leaders estimates have better prediction power in forecasting the out-of-sample likelihood of future M&A announcements than a naïve model with equal probability of future M&A announcements.

**Table 1.1** An Example of Serial Leaders

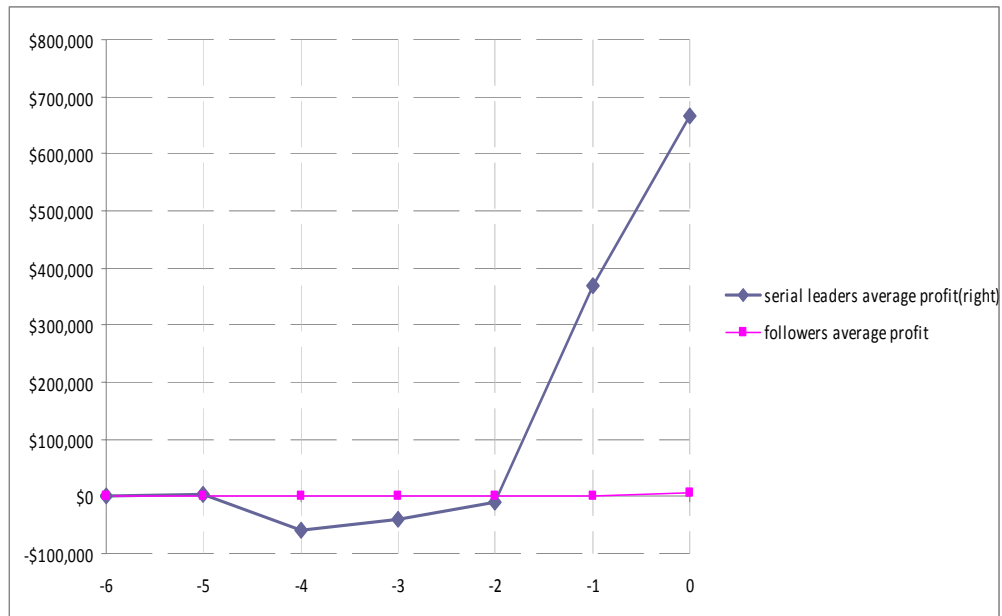
Name	Type	Variable	Estimate	WaldChiSq	Prob>ChiSq
BEAR, STEARNS & CO. INC.	4	Intercept	-1.577633	1136.2559	0.00
		Yt-Yt-1	0.000017	23.7730	0.00
		<b>Yt-1-Yt-2</b>	<b>0.000023</b>	20.2936	0.00
		Yt-2-Yt-3	-0.000001	0.0301	0.86
		Yt-3-Yt-4	-0.000003	0.5702	0.45
		Yt-4-Yt-5	0.000003	0.3208	0.57

Figure 1.5 gives an example of a serial leader's quarterly holding changes in some target firm before and after M&A announcements and their cumulative profits over the quarterly window. These two serial leaders are both brokerage firms. We can see the significant jump of holding positions 5 or 6 quarters ahead, and the huge profits these two firms make by accumulating the target firm shares early enough at a relatively low price and pocket the premium eventually.



**Figure 1.5** An Example of Serial Leader's  
Position Changes before M&A

Does it pay to be a serial leader? In Figure 1.6, I compute the average profit from all serial leaders and compare with the average profits from non-serial leaders (followers) over quarter window  $[-6,0]$ , where quarter 0 is the announcement quarter. The serial leaders' average profit goes from \$1,000 to nearly \$700,000 over the six quarters, but the followers' average profit only goes from \$0 to \$6,500 over same period. The magnitudes of holding positions by serial leaders are also dramatically larger than others. One possible reason is the size effect where serial leaders are mostly large institutions and followers are small ones. This is not fully justified because followers include insurance companies which are in general also large in size.



**Figure 1.6** Average Profit of Serial Leaders and Followers over quarter [-6,0]

#### 1.4.4 Probability of Informed Trading

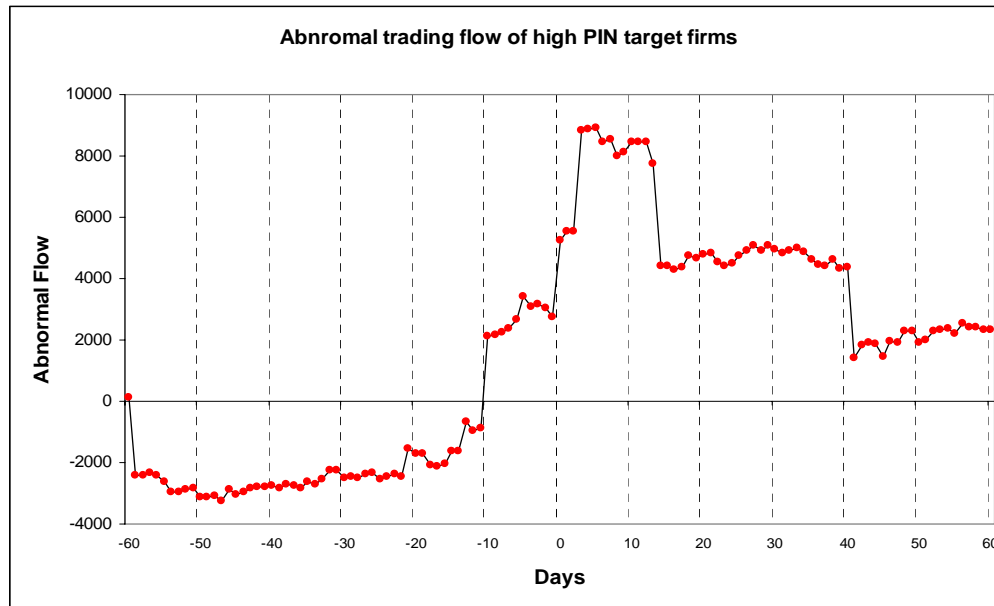
Probability of informed trading (PIN) is estimated by tracking on the net buying imbalances in the time series of a trading process. I examine the correlation between the probability of informed trading and institutional daily trading flows. Table 1.2 provides the correlation table. The correlation between PIN and institutional net trading imbalances is -0.53, and the correlation between PIN and institutional ownership is -0.27. These negative correlations imply that, in general, a high institutional trading imbalance (net buy) or high levels of institutional ownership are correlated with low levels of probability of informed trading. This is consistent with

the empirical fact that most institutions prefer large and liquid firms, which empirically have less probability of informed trading.

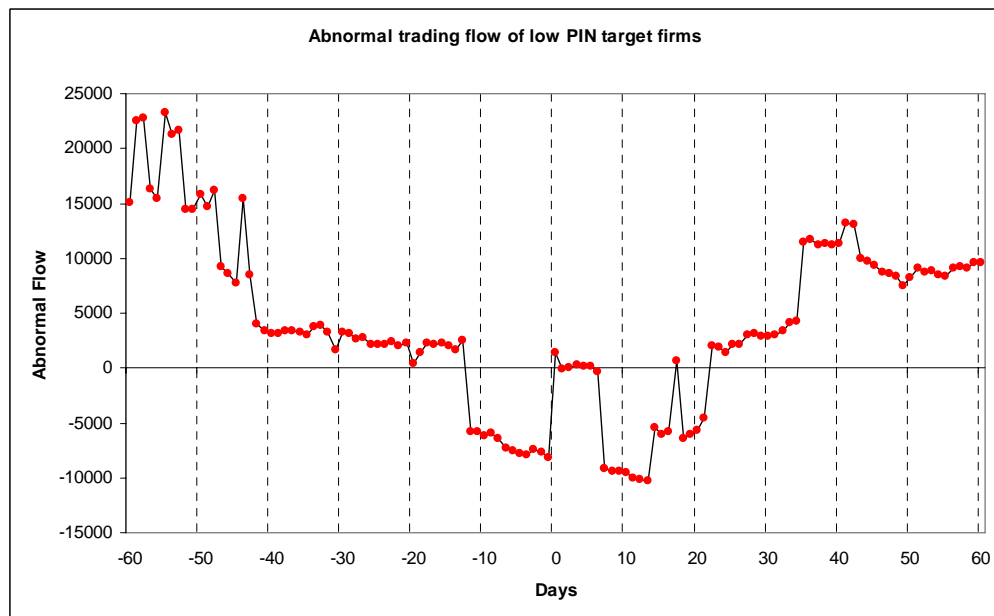
**Table 1.2** Correlation Matrix of PIN, Institutional Ownership Level and Daily Institutional Flow

	Pearson Correlation Coefficients		
	Prob >  r  under H0: Rho=0		
	<b>PIN</b>	<b>Ownership</b>	<b>Daily Flow</b>
<b>PIN</b>	1	-0.272	-0.530
		<.0001	<.0001
<b>Ownership</b>		1	0.009
			<.0001

To test for the first hypothesis that institutional investors are in fact informed traders, I sort contemporaneous PIN into 10 deciles and plot the abnormal institutional trading flow over the event period for target firms with highest PIN deciles (>70%), as shown in Figure 1.7a. The institutional trading flow pattern for high PIN firms is very similar to the patterns of informed institutional trading flow shown in Figure 1.2, therefore I do not reject the null of the first hypothesis and concludes that institutional investors are in fact informed traders. Figure 1.7b shows that institutional trading for low PIN firms does not similar pattern as in Figure 1.2.



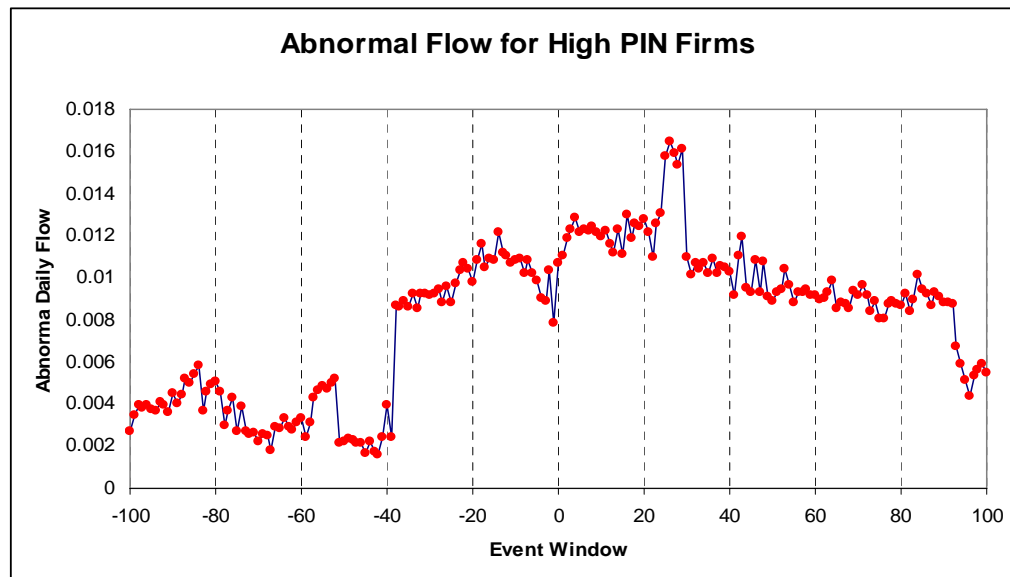
**Figure 1.7a** Abnormal daily net buying imbalances for high PIN target firms in contemporaneous year



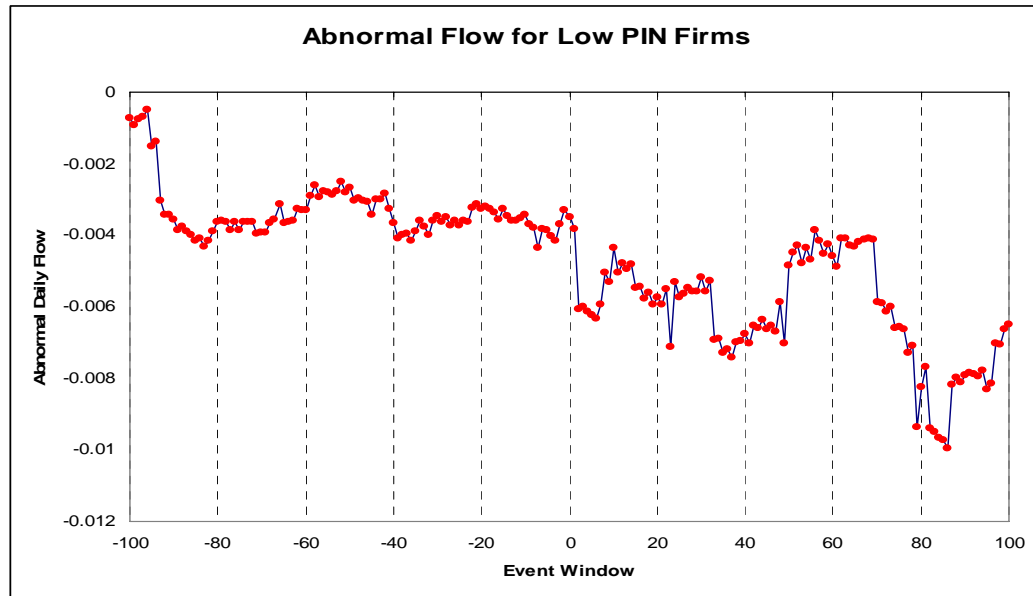
**Figure 1.7b** Abnormal daily net buying imbalances for low PIN target firms in contemporaneous year



For target firms that exhibit different degrees of information asymmetry, controlling for other characteristics, institutional trading patterns are surprisingly similar among firms that are characterized by high PIN in the year before a takeover event., as a test to hypothesis two, Figure 1.8a and Figure 1.8b show institutional abnormal daily net buying imbalances for target firms that have high and low PIN one year before an event. Figure 1.8a shows that institutional significant front-running behavior is associated with target firms that have higher PIN – a pattern that is consistent with institutional trading shown in Figure 1.2 – therefore I do not reject the null of the second hypothesis. Figure 1.8b shows that institutional trading on target firms with low PIN does not exhibit a similar pattern.



**Figure 1.8a** Abnormal daily net buying imbalances for high PIN target firms in previous year



**Figure 1.8b** Abnormal daily net buying imbalances  
for low PIN target firms

## 1.5 Conclusion and Further Research

To insure financial market fairness and integrity, the US Securities Act of 1934 requires institutional investment managers with investment discretion over \$100 million or more of certain equity securities to disclose their equity holdings at the end of each quarter. The SEC can use this information to analyze the influence and impact of institutional investment managers on the securities market. However, quarterly reports, due to their low frequency, reveal little about the impact of institutional investors on the securities trading process when they enter and exit some positions quickly within a quarter.

Campbell, Ramadorai and Schwartz (2008) develop a methodology that combines intraday NYSE TAQ data with institutional quarterly equity ownership reports to infer the high frequency daily equity holding positions of institutional investors. Using a similar technique, this paper investigates the high frequency trading behavior of institutional investors before and after M&A announcements.

This paper addresses four questions on institutional trading around M&A announcements. First, do institutional investors exhibit significant trading imbalances (buy-sell) before and after M&A announcements? Second, is the abnormal trading volume by institutions market participation or profit exploitation? Third, which types of institutional investors are more likely to learn material non-public information – banks, mutual funds, brokerage firms, or insurance companies? Fourth, how do we distinguish institutional investors inside information from their superior models? Can we further identify suspicious serial leaders who can consistently predict future M&A deals? Finally, is the significant front-running pattern of institutional investors associated with higher degree of information asymmetry among target firms?

My findings are summarized as follows. First, almost all institutions build up net buying positions as early as 30 days before an announcement, and most of them (except investment advisors) immediately reverse their positions on the announcement day. Second, there is no market-wide information leakage prior to the event, and prices of target firms do not jump immediately to the level of acquiring prices, however, institutional investors exhibit significant net buying imbalances prior to the event, which implies that they are trading on private information. Third, institutional

investors are not a homogeneous group in terms of trading strategies, regulation rules, or information venues, but, surprisingly, exhibit similar trading patterns before and after M&A announcements. Banks, insurance companies and mutual funds immediately reverse their positions on the announcement day, acting as “short term profit takers.” Investment advisors (brokerage firms) are slightly different since, after an announcement, they tend to be merger arbitragers, continuing to buy more shares of target firms in order to speculate on final deal consummation. Fourth, to distinguish inside information from superior models, I find institutional investors actually sell the forecasted target firms from an acquisition probability model and only buy the actual future targets. Further, there exist serial leaders who can consistently predict the future M&A deals and accumulate shares of target firms over a five-quarter period before the deal is announced. The serial leaders’ holding changes have explanatory power in forecasting the likelihood of actual M&As by a logit model. Finally, using the probability of informed trading (PIN) as a proxy to measure the cross-sectional degree of information asymmetry, I confirm that significant institutional front-running behavior is associated with target firms that have higher PIN over same period; I also find that stocks in general are characterized by different degree of information asymmetry exhibit similar patterns of systematic front-running patterns of institutions.

One caveat of this study is that daily institutional trading flow is not directly observed from any database, but rather it is inferred from a regression methodology developed by Campbell, Ramadorai and Shwartz (2008). This methodology is better than simple cutoff rules for distinguishing institutions from individuals in NYSE TAQ data, since it is more consistent with the institutional ownership report to SEC. It is

also better than any proprietary dataset because it allows for a less constrained time period and an increased breadth of institutions it covers. But most of my findings are consistent with conclusions I obtain by using quarterly data. For example, the logit model shows that serial leaders have inside information to be able to consistently predict actual targets and brokerage firms act as merger arbitrageurs. The trading behavior by most types of institutions exhibit similar patterns either at daily frequency or at quarterly frequency around M&A announcement.

However, the inferred trading flows have estimation errors and will never be precise. Because of this, I do not use the complementary positions in the trading process to represent the trading behavior of individual investors, which, once they become available, will constitute another interesting resource for comparing the trading behavior of institutions and individuals around M&A announcements. This methodology also excludes stocks from NASDAQ, due to difficulties in classifying the direction of trade. Nevertheless, it is the best methodology available so far to directly infer institutional trading flows from publicly available data sources.

The systematic trading patterns of institutional investors I find in this paper do not reveal how they obtain their information before an event. Are they simply smarter, with better models, or with more research into target firms, or better information venues, or do they simply have more information due to their frequent exposure to management teams?<sup>21</sup> Further detailed data is necessary to answer questions of where

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<sup>21</sup>As a corporate advisor for M&A deals, a full service investment bank may simultaneously advise a corporate client on a transaction; provide or raise financing to support the transaction (either on its own balance sheet or by sourcing capital from clients of the bank); trade in the shares of both the bidder and the target; offer equity research on both the bidder and the target; provide prime brokerage to hedge

they obtain their information and how that information travels. Whether what they do is legal or illegal is still an open question, to be answered by the SEC.

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funds and other investors wishing to trade in the shares of the bidder or the target; make a market in the shares of the bidder or the target, or otherwise invest its capital in trading positions that may be impacted by the transaction.

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## CHAPTER 2

### INSTITUTIONAL TRADING, INFORMATION AND MACROECONOMIC NEWS ANNOUNCEMENTS

#### 2.1 Introduction

In the US equity market, institutional investors are among the major players in the stock trading process, buying and selling stocks either as agents for their clients or as proprietary traders for their own accounts. In 2002, institutional holdings accounted for 57.9 percent of the total equity market value (Bernstein (2006)). As sophisticated investors with either better information venue or superior models, do institutional investors accumulate profitable positions before public news announcements and exploit market over-reaction or under-reactions afterwards? Do institutions differ in their trading behavior by trading strategies and fiduciary types? How do they trade when there is high opinion heterogeneity in the market?

Using quarterly report data (13F) filed to the US SEC, past literature has revealed some of the trading strategies by institutional investors, such as buying large and more liquid firm stocks. However, the quarterly frequency will not capture any trading behavior within a quarter, when there are some major events that have a significant impact on the market, such as the announcements of corporate news or macroeconomic news. This paper investigates the high-frequency trading behavior of institutional investors over 22 types of macroeconomic news announcements in the US equity market.

There are three empirical papers related to this paper: Campbell, Ramadorai and Vuolteenaho (2005), Campbell, Ramadorai and Schwartz (2007), and Pasquariello and Vega (2005). The first two papers developed the CRS methodology to infer the institutional trading flow at daily frequency and examined institutional trading behavior on earnings announcements, while the third one focuses on the information role of macroeconomic news announcements in US Treasury bond market, without identifying market participants. This paper makes several additional contributions. First, I look at trading on market-wide news that affects the whole equity market, and see how the information is incorporated into price through the trading process. Second, I further break down the information environment by heterogeneity of beliefs and by private information to differentiate the trading behavior of institutions. Third, comparing to Pasquariello and Vega (2005), I tested the informational role of macroeconomic news on the US equity market through the trading behavior of institutions.

I have three major findings: First, in aggregate, institutions do not always have informational advantage to make significant profits before macroeconomic news announcements, except in cases of certain empirically influential news like Retail Sales, Durable Goods Orders and Non-farm Payroll Employment. Therefore, they do not always trade in the right direction of market reaction. Second, institutional trading is highly correlated with heterogeneity in opinions about news announcements. If there is high dispersion of opinions among market participants before some negative news is released, institutions trade actively before the release of the news to make abnormal profits. Third, in cross-section, institutional trading is highly correlated with probability of informed trading, firm size and bond-like features of stocks. Institutions

trade more aggressively on bond-like stocks when there is macroeconomic news since these stocks are more likely to react to shocks in the macroeconomic news and therefore create trading opportunities. For stocks that have high probability of informed trading, institutions trading is positively associated with the negative news announcement.

The organization of the paper is as follows. Section 2.2 briefly reviews related literature. Section 2.3 develops testable hypotheses based on a theoretical framework. Section 2.4 describes data and conducts event studies of institutional trading behavior on macroeconomic news announcement. Section 2.5 summarizes the results and checks robustness. Section 2.6 concludes.

## **2.2 Related Literature**

### **2.2.1 Institutional Trading**

Past research has used quarterly levels and changes of institutional equity holding positions from 13F reports to measure institutional investors' preferences over time and cross-sectionally in US stock market. For example, studies show that institutional equity holdings are positively serially correlated, and positively correlated with lagged stock returns over a long time period (Sias (2004), Grinblatt, Titman and Wermers (1995), Wermers (1999, 2000), Nofsinger and Sias (1999), Badrinath and Wahal (2002)). But given the low frequency of quarterly data, it is hard to interpret these correlations because institutions can buy or sell stocks within the quarter and we can not tell whether this behavior was driven by a priori private information about the

news or by momentum trading in following the trend after the news announcements. There are other studies using proprietary datasets to measure the high-frequency institutional behavior. Froot, O'Connell and Seasholes (2001), Froot and Ramadorai (2007) and Froot and Teo (2007) used custodial data from State Street corporation; Lee and Radhakrishna (2000) used TORQ data; Kaniel, Saar and Titman (2004) and Boehmer and Wu (2007) used Consolidated Audit Trail data from NYSE; Griffin, Harris and Topaloglu (2003) used trades from NYSE brokerage houses; These studies are difficult to replicate and their samples are restricted in their coverage of institutions, the time period they could investigate, and stocks they could cover etc.

High frequency NYSE TAQ data has been explored to infer trading behavior of small or large traders in the equity market. For example, Gao (2005) studied trading behavior around IPO stocks lockup expiration dates. Gao and Oler (2007) studied trading behavior of selling target stocks before acquisition announcements. Shanthikuma (2004) studied trading behavior around earnings announcements of large and small traders, using a simple cutoff rule by trading size to categorize the investors. However, these studies did not categorize who initiated large or small trades.

### **2.2.2 Macroeconomic News**

Modern capital market theory has suggested that any systematic factors or “state variables” that affect the economy’s pricing operator or influence dividends or complete the description of state of nature will influence stock market returns (Ross (1976)). Chen, Roll, and Ross (1985) investigated a set of macroeconomic variables as systematic risk factors priced in asset returns: term structure of interest rates, inflation,

industrial production, and corporate bond default premium. Other papers have confirmed more influential macroeconomic variables such as PPI, unemployment, balance of trade, housing starts (Cornell (1983), Chen (1991), Pearce and Roley (1985), and Flannery and Protopapadakis (2002)).

Innovations in macroeconomic variables may indicate changes in either the states of economy or discount factors or future cash flows, and therefore may have a permanent impact on the long-term equilibrium of asset prices. For example, an economic expansion is good but an overheated economy could lead to fear of inflation. If this is true, then the trading flows over the news announcements days should reflect the information content in the news about the changing states of the economy. Recent papers have used macroeconomics forecast data such as MMS to study the information content by abnormal trading flows around macroeconomic news announcements in various markets. For example, Pasquariello and Vega (2006) studied order flows in the US Treasury bond market; Anderson, Bollerslev, Diebold and Vega(2003) studied order flows in the foreign exchange market; Green (2004) and He, Li, Wang, and Wu (2007) studied order flows in the US government bond market at an intraday level. These studies conclude that these markets are responding significantly to innovations in macroeconomic indicators over short term window. If we believe that markets are integrated to some degree (at least in US), then we would expect similar results in the US equity market. So far there has no event study done on abnormal trading flows around macroeconomic news announcements days in the US equity market. This current paper fills the gap in the literature and focuses on the institutional investors trading behavior.



### 2.3 Hypothesis Development

In equity markets, heavy trading around firm-specific news is closely related to information asymmetry, where some investors possess a priori private information about the news, e.g., Merger and Acquisition announcements. In another paper I tested the institutional trading flows around M&A events and showed significant information leaks before the announcements, especially on the target firms (Li (2007)). However, macroeconomic news is more transparent in the sense that the release of news is a scheduled market event at a fixed time and no one should be able to trade profitably beforehand. If there were abnormal institutional trading in the direction of news a priori, that should indicate institutional investor have private information.

In late summer 2007, investors became more concerned about mortgage-backed investments on highly-risky sub-prime mortgages, which were causing a credit crunch in the US stock market. From July 16 to Aug 21, DJIA went from 13950 to 13090, down by 6%. On Aug 24, 2007, the Bureau of Census released some macroeconomic news that showed increased numbers in new home sales and durable good orders from the previous month. The stock market bounced up immediately: DJIA went up by 2.3% for the week, Nasdaq by 2.9%, and S&P500 by 2.3%. 29 out of DJIA 30 stocks showed gains. In fact, two to three days before the macro news release, the market had been trading upwards.

In a frictionless market, once macroeconomic news is announced, asset prices should adjust immediately to the new long-term equilibrium price level that corresponds to shocks in the news. However, in a short-horizon window, we not only

see price jumps at the announcement time but also price fluctuations several days before and after the announcement. In a market with frictions, this behavior can be explained by asymmetric information among investors in the market, or by differences in opinions in interpreting the same information. In the stock market, it is natural to assume that large institutional investors usually have informational advantage over individual investors, either through their superior models and better information channels, or through their professional skills in understanding the investment environment. By examining abnormal buying or selling orders initiated by these large institutions, I can test the following hypotheses.

*Hypothesis 1: Stock market does not react significantly to macroeconomic news, either good or bad news.*

Since the development of Arbitrage Pricing Theory (Ross (1976)), past studies have shown that the stock market reacts significantly to some influential macroeconomic news, such as PPI, unemployment rate, term structure, inflation, balance of trade, housing starts etc (Chen, Roll, and Ross (1986), Cornell (1983), Chen (1991), Pearce and Roley (1985), and Flannery and Protopapadakis (2002)). The US treasury bond market and the foreign exchange market both react strongly to innovations in macroeconomic indicators (Pasquariello and Vega (2006), He, Li, Wang, and Wu (2007), Anderson, Bollerslev, Diebold and Vega(2003)).

The financial markets' responses to macroeconomic news are not surprising. Macroeconomic news is important in itself as indication of discount rate changes or future cash flow changes, or because it conveys information that can be used to update

forecasts about other aspects of general economic and investment environment. A quote from BusinessWeek on non-farm payroll employment announcement states: “The Labor Dept's monthly roundup of job market activity has always been the economics report Wall Street listens to more than any other. It's a market-mover because of its timeliness, breadth of coverage, and its influence over policymakers at the Federal Reserve.”

To detect any abnormal trading pattern of institutions, the definition of good/bad news is critical since it is related to the superior information that institutions may possess before the news is announced and therefore determines how the institutions will trade around the news. In earnings announcement event studies, the standard approach is to use the surprise measure, which is the standardized difference between actual earnings and consensus analyst earnings forecasts. If the surprise is positive, that is good news. Otherwise it is bad news. One reason this measure is widely used is that market participants closely watch the corporate earnings surprise measure and respond positively/negatively for companies that beat/fail to beat the analyst earnings forecast.

In our case of macroeconomic indicators forecast, it is less clear for two reasons. First, in general, good news to the economy such as increase in GDP will be thought as good news to the stock market as well. However, the increase in GDP may induce the fear of rising interest rates, which is “bad” news to the stock market.

In some cases, an announcement that is associated with higher stock and bond prices might be thought to be “good”, even if it is “bad” news to the economy. For

example, stock market rises on increased unemployment which we otherwise think of as “bad”. Or a tightening of the Fed Funds Rate both raises bond prices (“good”) and lowers stock prices (“bad”). Second, it is not so clear whether most market participants watch the MMS forecasts as their benchmark to measure the “surprise” of news.

In this paper, I tested four ways to classify good/bad news: (1) standardized surprises between MMS forecasts and realization; (2) monthly announcement changes; and (3) market abnormal return on news announcement day; (4) regression of market return on past surprises and monthly/quarterly/yearly changes. In fact, these four measures are not always in the same direction. The correlation matrix of the first three measures shows that in some cases, the surprise measure in (1) is in the opposite direction of market response measure in (3), which supports our hypothesis that the market does not always watch the surprise measure defined as the difference between MMS forecast and realization of indicators.

My objective function is to maximize abnormal profits of institutional investors by formulating trading strategies that can forecast the market reactions on the release of macroeconomic news. Using the market reaction on the event day to determine whether the market thinks it is good or bad news is an ex-post measure, which helps us to understand how the equity market incorporates the macroeconomic news shocks into asset pricing process. However, since it is ex-post, institutions who may want to trade on certain stocks that react strongly to macroeconomic surprises can not observe the market reaction ex-ante. Earlier studies (Cornell (1983)) have compared MMS forecasts with time series ARIMA forecasts and concluded that the MMS survey forecast errors have higher correlation with changes in asset prices than

forecast errors derived from an ARIMA model do. These studies have shown that MMS forecasts are an unbiased measure and the forecasting errors are smaller than a simple ARMA model, so another choice is to use the surprise measure between MMS forecasts and realizations. Unfortunately this measure also suffers the ex-post problem because 10 days before the release of any news, the institutions can only use some forecasting variables, either MMS or their own model forecasts, to build up positions. A preliminary analysis using surprises of macroeconomic announcements shows that the equity market does not always respond significantly to good or bad news, in some cases it bounces up in both cases just as non-announcement days. So it is hard to justify market reactions solely based on the surprises in news, especially ex-ante.

*Hypothesis 2: Institutions do not have private information or better ability to forecast some of the good or bad macroeconomic news before it is announce, therefore they do not formulate profitable trading strategies.*

The institutions in our study are confined to five types of institutions defined by 13f data: (1) bank, (2) insurance company, (3) investment company (mutual fund), (4) investment advisors (major brokerage firms), (5) others, including pension funds and university endowments. Given their size (about 60% of equity market value) and resources, these institutions conduct internal research using their own quantitative “superior” models and obtain external sources of information from sell-side analysts and corporate managers. In terms of “private” information that the institutions may possess on macroeconomic indicators, it is not inside information in the sense of trading individual stocks. Besides in-house technical analysis and external information, some institutions such as the brokerage firms are able to observe actual

order flows in the market therefore extract or infer valuable information. Past studies have documented institutional trading lead stock returns, and firms with increased institutional ownership outperform firms with decreased institutional ownership by 8.06% annually (Gibson and Safieddine (2003)).

*Hypothesis 3: Institutions trade less on high-information-heterogeneity days, on large firms, and on high-private-information (PIN) firms. There is no spillover effect from macroeconomic news to firm-specific news.*

Market microstructure literature examines how private information on specific stocks is incorporated into prices through the trading process. Probability of informed trading (PIN) can be estimated by a structural model explicitly, following procedures given by Easley, Kiefer and O'Hara (1996) and Easley, Hvidkjaer, and O'Hara (2002). Vega and Wu (2006) showed that stock information asymmetry using measures such as PIN increases on macroeconomic announcement days, which suggested macroeconomic news and other market-wide news played an important role in the formation of information asymmetry.

In general, if a stock has higher probability of informed trading, do institutions trade more or less in the stock? On days when there are unanticipated shocks in macroeconomic fundamentals, do high-PIN stocks react more strongly to the news than low-PIN stocks? I include the PIN measure in this paper to answer these questions.

Heterogeneity in opinions simply implies that even though investors observe

the same public information, they may still have different opinions or differential information in interpreting public news, which could lead them to initiate buying or selling orders in the equity market upon news announcements (Sarkar and Schwartz 2007). Grundy and McNichols (1990) and Shalen (1993) show that dispersed opinions magnify the effect of noisy information on price changes. Pasquariello and Vega (2006) use this measure to find that when the dispersion of beliefs on macroeconomic news forecasts among market participants is high, the contemporaneous correlation between order flow and bond yield changes in US bond market is higher. This paper addresses whether the level of information heterogeneity in the equity market will affect the institutional trading behavior.

On days when market participants disagree more on the direction and magnitude of forecasted news, there should be more trading on both buying and selling sides than on days when people disagree less and therefore trade in one direction if they are better informed traders such as institutions. We hypothesize that institutional trading is highly correlated with heterogeneity in opinions on macroeconomic news. In the cross-section, consistent with the literature, institutions usually prefer large stocks over small stocks. We hypothesize that institutions will buy large stocks most of the time whether it is good or bad news. Therefore, they may make or lose money depending on how the market goes. In case of small stocks, institutions should decrease their holdings over time, but small stocks are more likely the ones that institutions have private information on, so it is hard to predict whether they will make abnormal profits or not. For stocks that have high probability of trading on private information, we hypothesize that institutions are able to trade in the right direction before good/bad news are announced and make positive profits in both

cases. For stocks that have low probability of trading on private information, institutions should lose money in aggregate.

## **2.4 Data and Methodology**

Four data sources are used in this study: NYSE Trade and Quote (TAQ), Institutional Ownership (13F), CRSP, and International Money Market Services (MMS)<sup>22</sup> from 1993, when the 13F reports started, to 2004. NYSE TAQ and 13F data are combined to estimate and infer daily buy/sell order flows for institutional traders, following procedures described in Campbell, Ramadorai and Vuolteenaho (2005). CRSP is used to calculate abnormal stock returns. MMS data contains 22 major macroeconomic announcements. My sample includes 2837 firms that are traded in NYSE and reported quarterly 13f to SEC, from 1993 to 2004.

My NYSE TAQ data includes all trades and quotes during normal trading time on common stocks and excludes all close-end funds, ADRs and REITs. I use Lee and Ready (1991) algorithm to classify direction of a transaction. For details on Lee and Ready (1991) algorithm, see Appendix A.

Institutional investment managers who exercise investment discretion over \$100 million or more must report their holdings on Form 13F with the SEC. In general, an institutional investment manager is: (1) an entity that invests in, or buys and sells, securities for its own account; or (2) a person or an entity that exercises investment discretion over the account of any other person or entity. Thomson

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<sup>22</sup> I thank Clara Vega for providing us the analyst dispersion data, which were not available in MMS.



Financial distributes digital database of the institutional quarterly 13F filings and decomposes institutional ownership structure into five groups: (1) bank, (2) insurance company, (3) investment company (mutual fund), (4) investment advisors (major brokerage firms), (5) others, including pension funds and university endowments.

CRSP daily files provided the share price, shares outstanding, exchange codes, stock and market returns, etc. I use CRSP PERMNO to match CRSP data to TAQ and 13F stocks that traded on NYSE and AEMX. I use CRSP value-weighted market return as our benchmark to calculate abnormal stock returns around the announcement events. Using equal-weighted market return generates similar results.

#### **2.4.1 Daily Trading Flow of Institutional Investors**

NYSE TAQ database does not include information on identification of each order, nor distinguish buy initiated orders from sell initiated orders. Lee and Radhakrishna (2000) (LR) proposed a set of cutoff rules in terms of trading size in dollar term to separate institutions from individual trades from high frequency intraday data such as NYSE TAQ or TORQ. They examined the performance of several cutoff rules in the TORQ data set, for example, upper and lower cutoffs of \$20,000 and \$2,500 are most effective in distinguishing institutions from individual trades in small stocks. Recently, Campbell, Ramadorai and Shwartz (2007) (CRS) developed a regression model to infer the institutional net trading flows at daily level, where they combine information from the intra-day NYSE TAQ data and the quarterly 13F institutional ownership data.

The CRS methodology is superior to simple cutoff rules in two ways: first, it

does not suffer any selection bias or restrictions by using high-frequency proprietary database; second, it does not suffer any low-frequency problem by using quarterly or monthly institutional ownership data. In this study, I used CRS methodology to infer intraday and daily institutional and individual trading flow. For details, please refer to Appendix B.

The daily institutional trading flows do not show a significant rising or falling pattern over the entire period<sup>23</sup>, so I compute the average daily net flow over the whole data period as the benchmark institutional trading level for each firm. A common practice in earnings announcement studies is to use average returns over a certain estimation period, or market-beta-adjusted returns, or Fama-French three-factor model adjusted returns as benchmarks for expected returns. However, in this study, macroeconomic news announcements are released monthly with a market-wide effect on equity trading. It is not necessary here to compute expected flow in a similar way, since most macro news occur at monthly frequency, using previous period average will automatically include abnormal trading around several same events. The abnormal daily institutional trading flow over event window is defined as the difference between daily flow and the long-term benchmark trading level:

$$E(F_i) = \frac{\sum_{t=0}^N F_{it}}{N} \quad (1)$$

$$AF_{it} = F_{it} - E(F_i) \quad (2)$$

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<sup>23</sup> For each firm, I ran regression of daily flow on a linear time trend. Most firms do not have significant time trend over time.

Where  $N$  is the number of daily flows for firm  $i$  over the entire sample period and it varies among firms. I categorize the abnormal daily flow for each event day by the signs of macro announcements surprises, and take the average of abnormal flow for each event day across firms sorted by positive and negative announcement surprises:

$$AAF_{jt} = \frac{\sum_{i=1}^N AF_{ijt}}{M}, j = +1, -1, M = \# \text{ of firms}, t \in [-10, +10] \quad (3)$$

Where  $AAF_{jt}$  is the average abnormal daily flow for surprise  $j$  on event day  $t$ . Note that the daily institutional trading flow for firm  $i$  on day  $t$  is defined as the net buying number of shares divided by the total number of shares outstanding for that firm on day  $t$ , i.e., it is the daily net turnover ratio of a particular stock they hold. Empirical results showed that over a long time period, institutions have gradually increased their ownership in large market cap stocks, which will translate into a positive net buy turnover ratio in most of the days in my measure. It is of course, only a proxy for what institutions do in reality. In fact, some institutions such as mutual fund or pension fund which are more likely “dedicated” or “quasi-indexing” funds will not re-balance their portfolios on a daily basis (it is of course extremely expensive in terms of transaction cost). But they may increase their holdings on those large stocks gradually over long time period, sometimes just enter a long position and wait. In that case my measure of daily flow will be more like a daily average measure of large positions they build periodically. Other institutions such as brokerage firms which are more likely “transient” fund will focus on arbitrage opportunities to maximize profits, so they may buy and sell stocks more frequently and I expect to see both net buying and net selling

activities over short time period.

I hypothesize that institutional trading behavior differs in response to macroeconomic news in two ways:

First, if a positive surprise is coming, institutions with priority information may have run-ups several days before the news release, and sell immediately after market has gone up to positive news therefore pocket profits by market-timing. If a negative surprise is coming, institutions may start to sell first, or may start to buy on negative news on event day, hoping to recover on the overreaction of market after the event.

Second, the general macroeconomic condition matters. If the economy is in an expansion period with consecutive positive news in the near past, a piece of negative news, even small, will cause some turbulence in the market. For example, Aug 2007 release of non-farm payroll figure showed small declines in construction and manufacturing employments, which was the first decline in four years, the DJIA dropped by 2% on the day of the release. Positive news in a recession period is likewise. There exists an asymmetry in the way that market reacts to positive or negative news in expansion versus recession economic period.

I test the first hypothesis by sorting the standardized surprises into three categories: positive, zero, and negative news. Daily abnormal institutional trading flows and daily abnormal market returns are computed for positive and negative news surprises, respectively.

I test the second hypothesis by running a regression of sum of abnormal daily trading flows over event window on macroeconomic news surprises, on lagged macroeconomic conditions, and on interaction terms of news surprises and economic conditions to control for the asymmetry in responses.

$$Y_{ijt} = \alpha_i + \beta_{1i} * SUR_{ijt} + \beta_{2i} * X_{i,t-1} + \beta_{3i} * SUR_{ijt} * X_{i,-j,t-1} + \varepsilon_{it} \quad (4)$$

Where,  $Y_{it}$  is the sum of daily abnormal flow over event window  $[-10, +10]$  for period  $t$  for firm  $i$ . And  $t = 1, \dots, T$ ,  $T$  is the last announcement for event  $j$  in our sample period.  $X_{i,t-1}$  is a vector of several macroeconomic announcements that represent the economic condition in period  $t-1$ .  $X_{i,-j,t-1}$  is the vector of macroeconomic announcements that excludes event  $j$ .

#### **2.4.2 Macroeconomic Data and Standardized News Surprises**

The International Money Market Services (MMS) Inc. collects expectations and realizations of macroeconomic indicators in US economy. Every week since 1977, MMS has conducted a Friday telephone survey of about 40 professional money managers, collected forecast of all indicators that to be released during the next week and reported the median forecasts from the survey. Previous studies such as Balduzzi et al (2001) have confirmed that MMS survey data are mostly unbiased and more consistent with forecasted variables than those from extrapolative predictions such as ARMA models.

Table 2.1 provides a summary of 22 major macroeconomic announcements, reported from 1980s to 2004. Table 2.2 shows the means and standard deviations of both realizations and expectations of macroeconomic indicators collected by MMS.

Announcement surprises are defined as the standardized difference between realized and median forecasts of each macroeconomic announcement, to control for the variation in measurement units. The standardized surprise with macroeconomic indicator  $i$  at time  $t$  is computed as:

$$S_{it} = \frac{A_{it} - E_{it}}{SD_i} \quad (5)$$

Where  $A_{it}$  is the actual announced value for indicator  $i$ ,  $E_{it}$  is the MMS median forecast, as a proxy for market expectation, and  $SD_i$  is the sample standard deviation of  $(A_{it} - E_{it})$ . Notice that the  $SD_i$  here is quite different with the standard deviation of professional forecasters, which measures the dispersion in beliefs when they forecast a particular indicator one week ahead.

Andersen, Bollerslev, Diebold and Vega(2003), Pasquariello and Vega (2006) used standardized macroeconomic news surprises to show that unanticipated shock to fundamentals in the economy will affect both foreign exchange rates and bond yields, and there exists an asymmetric sign effect – bad news has greater impact than good news, which relates to information processing and price discovery theories.

In this paper I used this measure to test the relationship between aggregate equity market returns and unanticipated shocks in macroeconomic indicators, and the

**Table 2.1** Macroeconomic News Announcements

<b>Announcements</b>	<b>Obs</b>	<b>Source</b>	<b>Dates</b>	<b>StDev</b>
<b>Real Activity (Monthly)</b>				
1. Retail Sales	233	BC	2/13/1985-6/14/2004	Yes
2. Nonfarm Payroll	234	BLS	2/1/1985-2/7/2004	Yes
3. Industrial Production	233	FRB	2/15/1985-6/16/2004	Yes
4. Capacity Utilization	195	FRB	4/18/1988-6/16/2004	No
5. Personal Income	233	BEA	2/20/1985-6/28/2004	No
<b>Consumption (Monthly)</b>				
6. New Home Sales	195	BC	3/29/1988-6/24/2004	Yes
7. Personal Consumption Expenditures	228	BEA	7/17/1985-6/28/2004	No
<b>Investment (Monthly)</b>				
8. Durable Goods Orders	233	BC	2/26/1985-6/24/2004	Yes
9. Factory Orders	198	BC	3/30/1988-10/4/2004	Yes
10. Construction Spending	193	BC	4/1/1988-7/1/2004	Yes
11. Business Inventories	194	BC	4/14/1988-6/15/2004	No
<b>Net Exports (Monthly)</b>				
12. Net Exports	192	BEA	4/14/1988-6/14/2004	No
<b>Price Indices (Monthly)</b>				
13. Producer Price Index	236	BLS	2/15/1985-6/17/2004	Yes
14. Consumer Price Index	237	BLS	2/26/1985-10/19/2004	Yes
<b>Forward Looking (Monthly)</b>				
15. Consumer Confidence Index	160	CB	7/30/1991-10/26/2004	Yes
16. NAPM Index	162	NAPM	2/1/1991-7/1/2004	Yes
17. Housing Starts	233	BC	2/19/1985-6/16/2004	Yes
18. Index of Leading Indicators	233	CB	3/1/1985-6/17/2004	Yes
<b>Unemployment (Weekly)</b>				
19. Initial Unemployment Claims	235	ETA	2/1/1985-7/2/2004	Yes
<b>GDP (Quarterly)</b>				
20. GDP Advance	57	BEA	4/27/1990-4/29/2004	Yes
21. GDP Preliminary	57	BEA	5/24/1990-5/27/2004	Yes
22. GDP Final	57	BEA	6/21/1990-6/25/2004	Yes

**Table 2.2** Summary Statistics for MMS Data

<b>Variable</b>	<b>Mean-Actual</b>	<b>StDev Actual</b>	<b>Mean-Forecast</b>	<b>StDev Forecast</b>	<b>Mean-Dispersion</b>	<b>StDev Dispersion</b>
<b>Real Activity(Monthly)</b>						
1. Retail Sales	0.3046	1.1343	0.3114	0.7464	0.3017	0.1581
2. Nonfarm Payroll	137.9103	176.6946	144.5923	111.5708	41.8140	14.2120
3. Industrial Production	0.4129	1.2843	0.4146	1.2463	0.1826	0.1347
4. Capacity Utilization	77.2979	16.8364	77.2638	16.8207	NA	NA
5. Personal Income	0.4371	0.3581	0.3968	0.2077	NA	NA
<b>Consumption(Monthly)</b>						
6. New Home Sales	774.7231	184.5824	762.9611	169.6725	19.2697	10.2353
7. Personal Consumption Expenditures	0.4329	0.5190	0.3998	0.3809	NA	NA
<b>Investment (Monthly)</b>						
8. Durable Goods Orders	0.5880	3.7137	0.4802	1.8248	1.0305	0.3364
9. Factory Orders	0.3569	2.1666	0.2833	1.8957	0.4992	0.2528
10. Construction Spending	0.3259	1.1376	0.1990	0.5164	0.5866	0.5773
11. Business Inventories	0.2443	0.3806	0.1969	0.2788	NA	NA
<b>Net Exports (Monthly)</b>						
12. Net Exports	60.2635	22.6657	59.7824	22.6360	NA	NA
<b>Price Indices (Monthly)</b>						
13. Producer Price Index	0.1528	0.4874	0.2109	0.2536	0.1297	0.0485
14. Consumer Price Index	0.2473	0.2026	0.2611	0.1480	0.0831	0.0509
<b>Forward Looking (Monthly)</b>						
15. Consumer Confidence Index	100.6813	26.0192	100.4472	25.3890	1.6457	0.6086
16. NAPM Index	52.0420	5.2218	52.0410	4.8292	0.9664	0.3031
17. Housing Starts	1.5133	0.2451	1.5016	0.2299	0.0415	0.0381
18. Index of Leading Indicators	0.1752	0.5238	0.1559	0.4099	0.1750	0.0901
<b>Unemployment (Weekly)</b>						
19. Initial Unemployment Claims	5.7128	0.9707	5.7592	0.9851	7.9733	5.4402
<b>GDP (Quarterly)</b>						
20. GDP Advance	2.6765	1.9747	2.3814	1.8523	0.4798	0.1696
21. GDP Preliminary	2.8140	2.1682	2.7420	2.0610	0.3133	0.1776
22. GDP Final	2.7980	2.2358	2.7706	2.1608	0.1279	0.0506



relationship between institutional trading behavior and these shocks. I confirm that equity market returns react significantly to unanticipated shocks to economic fundamentals, such as Retail Sales, Non-farm Payroll Employment, New Home Sales, Consumer Confidence Index, Advance GDP, and Durable Goods Orders. Also consistent with our assumptions, the equity market does not always react to economically “good” (“bad”) news in a positive (negative) way. For example, when Consumer Price Index incurs a positive surprise which means higher inflation, “bad” news for the economy, the equity market return actually goes up. In case of negative surprises in CPI, which is “good” news for lower inflation, the equity market return goes down.

#### **2.4.3 Information Heterogeneity**

I use the MMS standard deviation across professional forecasters to measure dispersion of beliefs among sophisticated investors. The standard deviation is only available for 17 macroeconomic indicators, as shown in Table 2. Following Pasquariello and Vega (2005), I construct monthly measures of information heterogeneity similarly based on 17 announcements, excluding the GDP announcements which are released by quarter. Initial Unemployment Claims are weekly measures so I average the dispersion of beliefs across four weeks to give a monthly figure. Then I define the monthly information heterogeneity level as a weighted sum of monthly dispersion across announcements, and categorized by 10 deciles to classify days in which there was a macroeconomic announcement.

$$SD_t = \sum_{j=1}^{17} \frac{SD_{jt} - \mu(SD_{jt})}{\sigma(SD_{jt})} \quad (6)$$

Where,  $SD_t$  is the standard deviation of announcement  $j$  across professional forecasts for month  $t$  in one year,  $\mu(SD_{jt})$  and  $\sigma(SD_{jt})$  are its sample mean and standard deviation across all 17 professional forecast dispersions in month  $t$ , respectively. Then I categorize all monthly announcement days into 10 deciles of information heterogeneity based on its empirical yearly distribution, assuming that the annual distribution of dispersion in opinions are different. I assume that dispersion of beliefs remains constant between each announcement.

Grundy and McNichols (1990) and Shalen (1993) show that dispersed opinions magnify the effect of noisy information on price changes. Pasquariello and Vega (2006) use this measure to find that when the dispersion of beliefs on macroeconomic news forecasts among market participants is high, the contemporaneous correlation between order flow and bond yield changes in US bond market is higher.

#### **2.4.4 Probability of Informed Trading**

Market microstructure literature examines how private information on specific stocks is incorporated into prices through trading process. Probability of informed trading (PIN) can be estimated by a structural model explicitly, following procedures given by Easley, Kiefer and O'Hara (1996) and Easley, Hvidkjaer, and O'Hara (2002). Vega and Wu (2006) showed that stock information asymmetry using measures such as PIN increases on macroeconomic announcement days, which suggested macroeconomic

news and other market-wide news played an important role on the formation of information asymmetry.

In general, if a stock has higher probability of informed trading, do institutions trade the stock more or less? On days when there are unanticipated shocks in macroeconomic fundamentals, do high-PIN stocks react more strongly to the news than low-PIN stocks? I include PIN measure in this paper to answer these questions.

Data with estimated annual PIN measures of NYSE/AMEX common stocks from 1983 to 2001 were obtained from Soeren Hvidkjaer's website, which were computed following procedures given in Easley, Kiefer and O'Hara (1996) and Easley, Hvidkjaer, and O'Hara (2002). I form 10 portfolios each year by categorizing PIN estimates into 10 deciles based on cross-sectional distribution within that year. Then I examine the abnormal returns and abnormal institutional trading flows on each PIN-based portfolio around macroeconomic news announcement days.

#### **2.4.5 Abnormal Profits**

Institutions form positions before macro news to take advantage of market reactions in their favor, if they could forecast the right directions of market movement. So I compute simulated abnormal profits over the event window for institutions by multiplying their cumulative abnormal flows with daily abnormal market returns. The formula is as follows:

$$\Pi_t = CAF_t * AR_{mt}$$

Where,  $CAF_t$  is cumulative abnormal flow on day  $t$ ,  
 $AR_{mt}$  is abnormal market return on day  $t$ . (7)

Cumulative abnormal flow is defined as the cumulative daily flow in excess of a long-run mean over entire sample period. Cumulative abnormal daily flow over any two-period interval  $[t_1, t_2]$  is calculated for positive and negative announcement surprises, respectively:

$$CAF_{(j, t_1, t_2)} = \sum_{t=t_1}^{t_2} AAF_{jt}, \quad (8)$$

$j = +1, -1$

Abnormal market return over event can be defined in many ways, such as taking the difference between daily market return and long-run mean of market return, or between daily market return over event window and market return over a previous period such as  $[-120, -30]$  as in earnings announcement studies literature. However, given that the macroeconomic news announcements are released at a monthly frequency, using a market return over a previous period as a benchmark will be easily overlapping with any abnormal responses from previous announcements. So before the news announcements, there should be an ex-ante measure on expected market return conditional on the past information. I use the following multivariate ARMA model to compute the conditional mean of monthly market return at any given time  $t$ :

$$R_t = \alpha + \sum_{j=1}^p \beta_j * R_{t-j} + \sum_{m=1}^M \sum_{i=1}^q \gamma_{m,i} * SUR_{m,t-i} + \varepsilon_t \quad (9)$$

$t = 1, \dots, T$

Where,  $R_t$  is monthly market return at time  $t$ , and time  $t$  is defined as 11<sup>th</sup> day before one announcement to insure event window of  $[-10,+10]$ . Before I ran this ARMA model, I tested the stationarity of  $R_t$  sequence by Augmented Dicky-Fuller test and it showed a stationary process.  $R_{t-j}$  is the monthly market returns of lag  $j$ , and  $p$  is the order of effective lags, which will be determined by BIC or AIC.  $SUR_{m,t-i}$  is the surprise measure of previous macroeconomic news announcements  $m$  at lag  $i$ , and  $q$  is the order of effective lags, which will be determined by BIC or AIC, and  $M$  is equal to the total number of macroeconomic announcements in a given month. Since the Initial Unemployment Claims are at weekly frequency and GDP figures are at quarterly frequency,  $M$  can be either 19, 22, or 25, and  $T = 12*250=3000$ .  $\varepsilon_t$  is White Noise residual.

I use the average market return over the entire sample period as the conditional mean of market return, which serves as a benchmark to compute the abnormal daily market returns over event window  $[-10, +10]$ . It has been argued that in practice for short-run event studies, how you control for risk does not matter that much, since in a short-run event study, the amount of systematic risk on a day or two is tiny relative to the size of the event. For example, if the market risk premium is 8% per year and there are 250 trading days then the daily premium is 0.00032, or a little more than 3/100 of a percent a day (Bernstein Research (2006)).

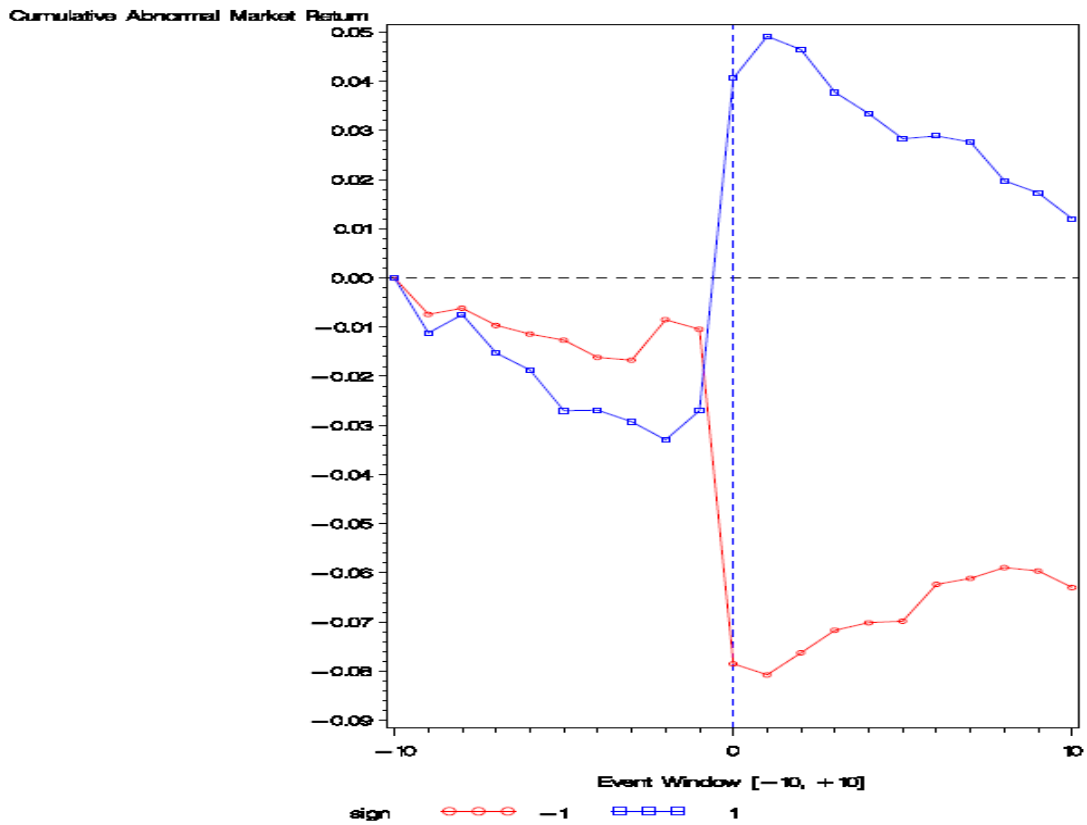
## **2.5 Results and Robustness Check**

### **2.5.1 Summary of Results**

The institutional daily trading behavior on macroeconomic news announcements depends on how we categorize the news and how we categorize the investment styles within these institutions.

First, I categorize positive and negative macroeconomic news by the reaction of aggregate market index on the announcement day. So by construction, I observe a positive jump on good news and negative one on bad news. More interestingly, after the news announcements, there is a clear pattern of market overreaction to both positive and negative news, in almost all news events. Upon seeing a piece of positive news, the abnormal market return increases significantly on the event day, but over the next 10 days, it starts to decline gradually, which implies that the market has overreacted to positive news in the first place. Similarly, upon a piece of negative news, the market return decreases significantly on the event day but then slowly picks up over next 10 days, which implies that market has overreacted to negative news as well. Figure 2.1 shows the cumulative abnormal market return over event window  $[-10, 10]$  for aggregation of some influential news.

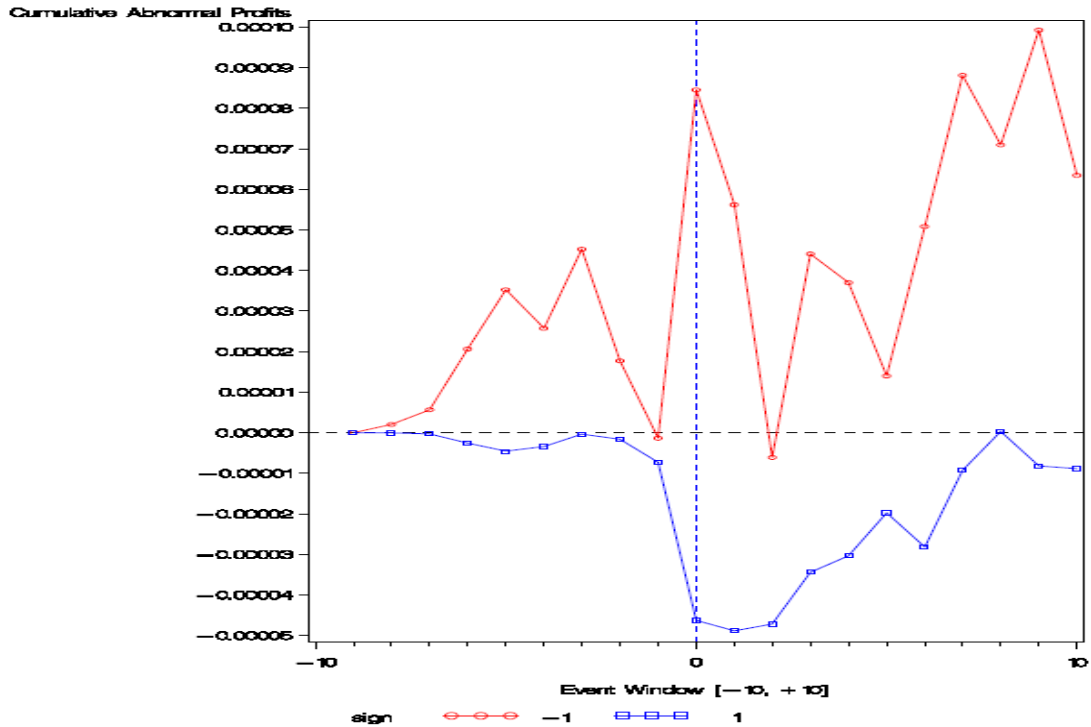
In aggregate, institutions have better ability in predicting some influential news such as durable goods orders, retail sales, CPI, and non-farm payroll employment. When there is negative news they start to build up a short position several days ahead



**Figure 2.1** Cumulative Abnormal Market Returns on Positive (Blue) and Negative (Red) Macroeconomic News

and make profit on the news release. In positive news, the institutions seem not be able to make much of profits before news release; but after the news release they are able to profit on the market overreaction to positive news. Figure 2.2 shows the abnormal profits that institutions make during these influential news announcements.

Second, I categorize macroeconomic news announcements by the signs of standardized surprises defined as the difference between MMS forecasts and



**Figure 2.2** Cumulative Abnormal Profits on Influential Macroeconomic News

realizations. In this case we do not always observe a positive (negative) response to a positive (negative) surprise by the aggregate market. In terms of institutional abnormal trading, the behavior is also mixed and results in either positive or negative profits. There are several possible interpretations to the mixed results: first, macroeconomic news surprises do not have a significant impact on aggregate stock market; second, institutional investors do not predict well market reactions to macroeconomic news; third, institutional investors trade more aggressively on exploiting arbitrage opportunities on firm-specific news rather than on aggregate market-wide news.

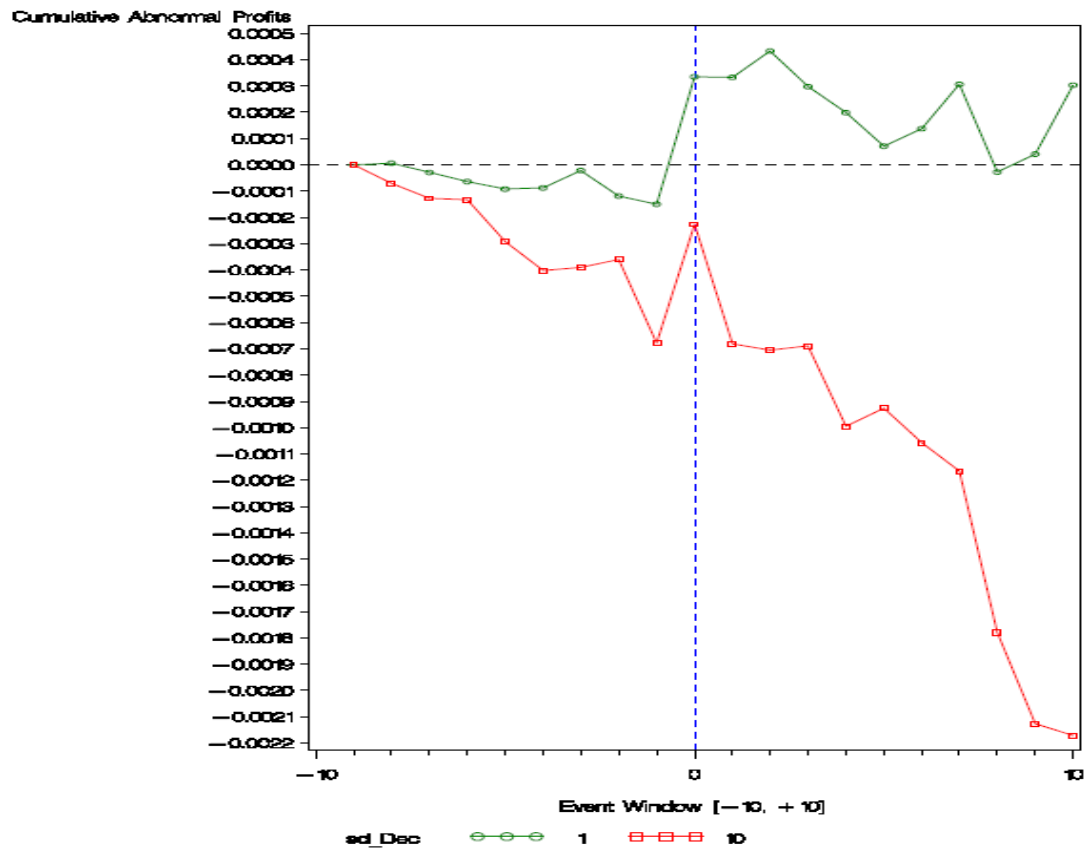
Past studies have shown that macroeconomic shocks significantly affect the



US government bond yields (Pasquariello and Vega (2006)). Moreover, Baker and Wurgler's (2006) find that the US government bonds co-move more strongly with bond-like stocks: stocks of large, mature, low-volatility, profitable, dividend-paying firms that are neither high growth nor distressed. Following their paper, I sort out these bond-like stocks and examine the institutional trading behavior on these stocks around macroeconomic news announcements. My findings are: first, bond-like stocks react strongly to shocks in macroeconomic news announcements; second, institutional investors trade on the reactions of bond-like stocks upon macroeconomic news to make abnormal profits.

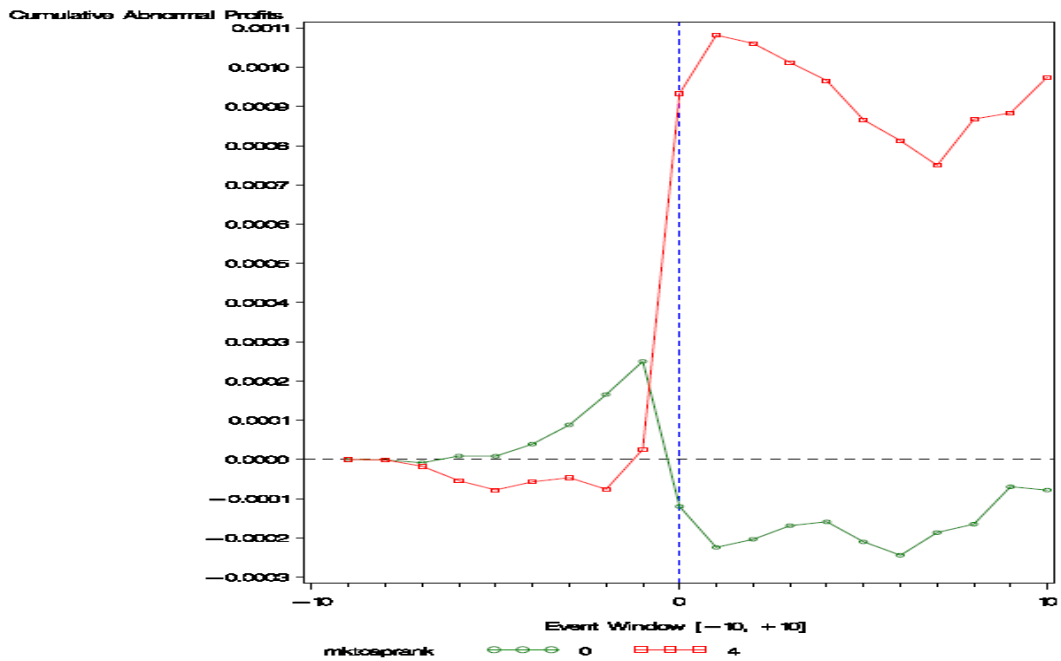
Institutional trading is highly correlated with heterogeneity in opinions on news announcements. If there is high dispersion of opinions in the news forecasts before it is released, when people disagree more on news, there will be lots of both buying and selling orders since it is harder to predict the direction of news and market reactions, but institutions are able to trade (either buying or selling) to exploit profitable opportunities, especially on negative news they make positive profits on highly dispersed opinions, as shown in Figure 2.3. However, on low information heterogeneity days when people agree most on the news, institutions tend to trade more around the announcement days but they fail to make a positive profit.

In the cross-section, institutional trading is highly correlated with private information, firm size and bond-like features of stocks. Institutions trade more aggressively on bond-like stocks when there is macroeconomic news announcement

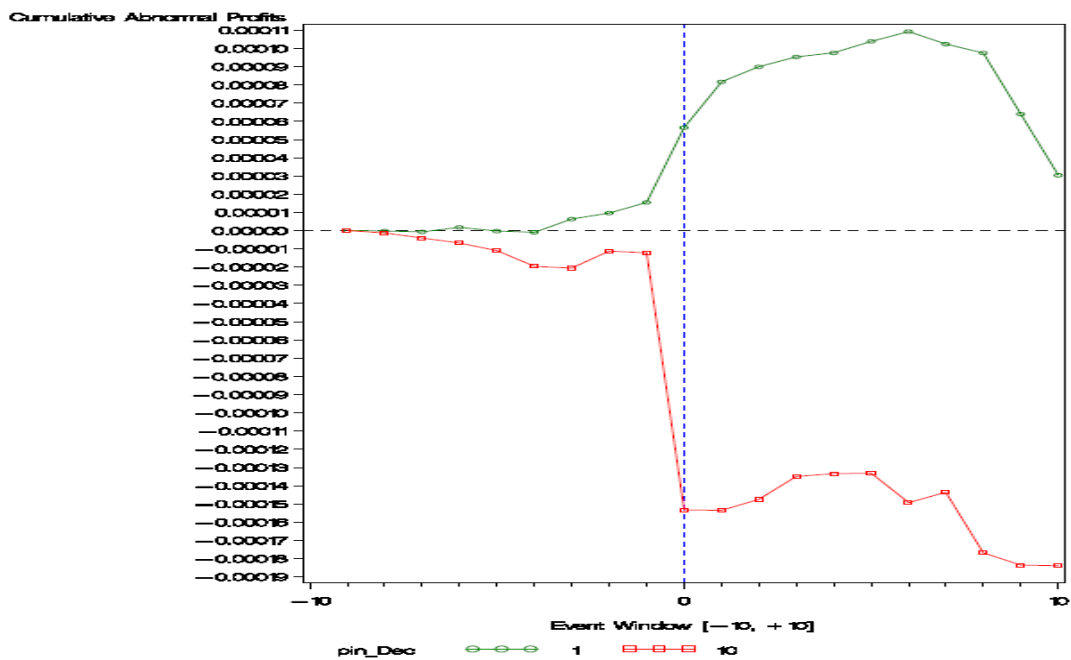


**Figure 2.3** Institutions Abnormal Profits in High (Green) and Low (Red) Information Heterogeneity Days

since these stocks are more likely to react to shocks in the news and therefore create arbitrage opportunities. Institutions tend to buy large firms and sell small firms over time no matter what kind of news will be released, as in Figure 2.4. For stocks that have high probability of trading on private information, institutions are able to always trade in the right direction before negative news is announced. But for stocks with low probability of informed trading, institutions make profits on positive news announcements, as in Figure 2.5.



**Figure 2.4** Institutions Abnormal Profits with Large (Red) and Small (Green) Firms



**Figure 2.5** Institutions Abnormal Profit with High PIN (Green) and Low PIN (Red) Firms

### 2.5.2 Robustness Check

Flannery and Protopapadakis (2002) refers to a “sequence hypothesis” where macro variables will be significant only if they are announced early each month, while later announcements would not be significant because they would add little to investors’ macroeconomic assessments. In my study I did not find evidence of sequential effects.

If the average or expected daily flow has been on a rising pattern several weeks before the announcements, then my measure of abnormal trading flow will be contaminated in two ways: first, if the expected daily flows calculated during estimation period is biased upward, then it will be hard to identify the statistical significance of abnormal trading flow during event period; second, if there were a sustainable upward trending in institutional trading flow (which was confirmed by the upward trend in quarterly institutional ownership data ), then abnormal trading flow will be falsely specified as correlated with macro announcements while there should be no correlation.

Following Monteiro, Zaman and Leitterstorf (2007), I used the following model to estimate the expected daily flow over estimation period:

$$V_{it} = \alpha_i + \beta_i * t + \varepsilon_{it} \quad (10)$$

Daily trading flow for firm *i* on day *t*, where *t* is over the estimation window [-120, -31]. Using 30 days before announcement is to avoid the possibility of capturing the effect of announcement-driven order flow run-ups several weeks before the

announcement.

I use OLS to estimate the model and compute t-stat to confirm/reject the null hypothesis that there is no linear time trend in daily order flow. If null is rejected, I use

$$E(V_i) = \alpha_i + \beta_i * t \quad (11)$$

If null is not rejected, I use

$$E(V_i) = \frac{\sum_{t=-120}^{-31} V_{it}}{90} \quad (12)$$

In fact, most of the null are not rejected so I use the average of daily flows over estimation period for each firm.

I calculate the abnormal flow in the following way for event window  $[-30, +30]$  for each firm:

$$AV_{it} = V_{it} - E(V_i) \quad (13)$$

Cumulative abnormal daily flow over any two-period interval  $[t_1, t_2]$  is calculated for positive and negative announcement surprises, respectively:

$$CAF_{(j, t_1, t_2)} = \sum_{t=t_1}^{t_2} AAF_{jt}, \quad (14)$$

$j = +1, -1$

Then I use several methods to test whether the cumulative abnormal flow is significant over the event period.

Patell's test assumes cross-sectional independence of abnormal flows, and there is no event-induced change in the variance of the event-period abnormal flows. Standardized CAF equal to CAF divided by the standard deviation of the estimation period abnormal flows.

$$SCAF_i = \frac{CAF_i}{\sqrt{T * Var(AF_{i, est})}}$$

$$t_{Patell} = \frac{\sum_{j=1}^N SCAF_j}{\sqrt{N}} \quad (15)$$

The test-statistic showed that the CAF is significantly different from zero.

## 2.6 Conclusion and Discussion

This paper conducts a series of event studies on the abnormal trading behavior of institutional investors in the US equity market before and after the release of macroeconomic news. Combining the NYSE TAQ intraday data with quarterly institutional ownership report, I inferred daily institutional trading flows (buy – sell) on their equity positions in 2837 firms from 1993 to 2004, I use a methodology developed by Campbell, Ramadorai and Vuolteenaho (2005). This methodology is superior to a simple cutoff rule in two ways. First, it uses public available data so it does not suffer any selection bias or restrictions by using a high-frequency proprietary

database; second, the daily institutional trading flows are more consistent with the reported quarterly institutional ownership changes.

With this daily institutional trading flow measure, I study their trading behavior around the announcements of 22 major macroeconomic indicators in US equity market to answer the following questions. First, do institutions have private information or better ability to forecast good/bad macroeconomic news before it is released? How do they trade when public news is released? Do they differentiate in their trading behavior by investment type or trading style? How do institutions trade when the market participants have highly heterogeneous or homogeneous opinions on public news forecasts? How do institutions trade in firms with high or low probability of informed trading?

My findings are as follows. First, in aggregate, institutions do not always have information advantage or superior models to forecast all macroeconomic news. But in the case of empirically influential macroeconomic news, such as retail sales, durable goods orders and non-farm payroll employment, institutions accumulate positions before announcement days and make profits on and after the announcement days. Second, on days when information heterogeneity among market participants is high, institutions make profits especially on the release of negative shocks in news. In the cross-section, institutional trading is highly correlated with private information, firm size and bond-like features of stocks. Institutions trade more aggressively on bond-like stocks when there is macroeconomic news since these stocks are more likely to react to shocks in the macroeconomic news and therefore create trading opportunities. For stocks that have high probability of informed trading, institutions trading is

positively associated with the negative news announcement.

Future work may extend the work to general macroeconomic environments. How market reacts to macroeconomic news may depend on general economic conditions such as business cycles and economic expansion or recession period. If the economy is in an expansion period, good news on macroeconomic conditions is well expected and should have little effects on market; however, good news in a contrarian period may lead to a huge positive response of the market. A regime-switching framework of the general economy may be applied to forecast the direction of equity market, and how institutions obtain information in different regimes.



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## APPENDIX

### **Appendix A** Buy and Sell Classification

The TAQ database of NYSE contains trade-by-trade data pertaining to all listed stocks starting in 1993. However, the TAQ database does not classify transactions as buys or sells. To classify the direction of a trade, I used the Lee and Ready (1991) algorithm. If the price of a trade is higher (lower) than the midpoint of the contemporaneous bid-ask quote, the trade is classified as a buy (sell). If the two are equal, the algorithm classifies trades on an up-tick as buys, downtick as sells. All zero-tick trades that can not be identified as buy or sell, plus the cancelled trades or batched or split-up trades that can not be classified by Lee-Ready algorithm, are put into a separate bin of unclassifiable trades. Following CRS, I categorize all buy/sell trades into 19 trade dollar-size bins whose lower cutoffs are \$0, \$2000, \$3000, \$5000, \$7000, \$9000, \$10,000, \$20,000, \$30,000, \$50,000, \$70,000, \$90,000, \$100,000, \$200,000, \$300,000, \$500,000, \$700,000, \$900,000, and \$1 million. I subtract sells from buys to get the net order flow within each trade size bin. I aggregate all shares traded in each of these dollar-size bins to daily frequency, and normalize each daily bin by the daily shares outstanding as reported in the CRSP database. Then I aggregate the normalized daily buy/sell volume to quarterly frequency. For unclassified trades, I aggregate and normalize the same way. The sum of buy, sell and unclassifiable turnovers is the TAQ measure of total turnover in each stock-quarter. Note: I excluded all stock-quarters for which TAQ total turnover as a percentage of shares outstanding is greater than 200 percent.

## **Appendix B Methodology**

The NYSE TAQ database does not include information on identification of each order, nor distinguish buy initiated orders from sell initiated orders. Lee and Radhakrishna (2000) (LR) propose a set of cutoff rules in terms of trading size in dollar terms to separate institutions from individual trades from high frequency intraday data such as the NYSE TAQ or TORQ. They examine the performance of several cutoff rules in the TORQ data set; for example, upper and lower cutoffs of \$20,000 and \$2,500 are most effective in distinguishing institutions from individual trades in small stocks. Recently, Campbell, Ramadorai and Shwartz (2008) (CRS) developed a regression model to infer institutional net trading flows at the daily level, in which they combine information from the intra-day NYSE TAQ data and the quarterly 13F institutional ownership data.

The CRS methodology is superior to simple cutoff rules in two ways: first, it does not suffer any selection bias or restrictions by using high-frequency proprietary database; second, it does not suffer any low-frequency problem by using quarterly or monthly institutional ownership data. In this study, I used CRS methodology to infer intraday and daily institutional and individual trading flow.

The CRS methodology follows the steps below:

1. Get NYSE TAQ intraday data, do a tick test as buy/sell/unclassified for each transaction.
2. Group buy and sell transactions separately by dollar size into 19 bins with lower cutoffs: \$0, \$2000, \$3000, \$5000, \$7000, \$9000, \$10,000, \$20,000,



\$30,000, \$50,000, \$70,000, \$90,000, \$100,000, \$200,000, \$300,000, \$500,000, \$700,000, \$900,000, and \$1 million.

3. Subtract sells from buys to get net order flow within each trade size bin.
4. Aggregate all shares traded in each buy/sell/net-flow bin to daily frequency, and normalize each daily bin by the daily shares outstanding as reported in the CRSP data.
5. Aggregate the normalized daily volume to quarterly frequency. Unclassified volume is done in the same way.

The change in the quarterly level of institutional ownership for a stock can be explained by a simple regression on past changes and levels of institutional shares for the stock, and the total buy, sell and unclassifiable volumes during the quarter:

$$\Delta Y_{it} = \alpha + \phi Y_{i,t-1} + \rho \Delta Y_{i,t-1} + \beta_U U_{it} + \beta_B B_{it} + \beta_S S_{it} + \varepsilon_{it} \quad (1)$$

Where,  $Y_{it}$  is the share of firm  $i$  that is owned by institutions at the end of quarter  $t$ ,  $\Delta Y_{it}$  is the change of institutional ownership between quarter  $t$  and  $t-1$ ,  $U_{it}$  is unclassifiable total trading volume,  $B_{it}$  is total buy volume, and  $S_{it}$  is total sell volume in stock  $i$  during quarter  $t$  (all variables are expressed as percentages of the end-of-quarter  $t$  shares outstanding of stock  $i$ ).

A more generalized version that includes all 19 trade-size bins and restricts the coefficients on buy and sell volume to be equal and opposite would be:

$$\Delta Y_{it} = \alpha + \phi Y_{i,t-1} + \rho \Delta Y_{i,t-1} + \beta_U U_{it} + \sum_z \beta_{Fz} F_{zit} + \varepsilon_{it} \quad (2)$$

Where,  $F_{it} = B_{it} - S_{it}$ , and  $Z$  indexes trade size bins. Following CRS, I use the Nelson and Siegel (1987) exponential smoothing function to reduce the number of coefficients to be estimated while retaining the ability to capture the shape suggested by the unrestricted specifications. This method requires estimating a function  $\beta(Z, v_{it})$  that varies with trade size  $Z$  and an interaction variable  $v_{it}$ , and is of the form:

$$\beta(Z, v_{it}) = b_{01} + b_{02}v_{it} + (b_{11} + b_{12}v_{it} + b_{21} + b_{22}v_{it})[1 - e^{-Z/\tau}] \frac{\tau}{Z} - (b_{21} + b_{22}v_{it})e^{-Z/\tau} \quad (3)$$

Defining  $g_1(Z) = [1 - e^{-Z/\tau}] \frac{\tau}{Z}$  and  $g_2(Z) = [1 - e^{-Z/\tau}] \frac{\tau}{Z} - e^{-Z/\tau}$ , I estimate the

function using nonlinear least squares, searching over different values of  $\tau$ , to select the function that maximizes the  $R^2$  statistics:

$$\begin{aligned} \Delta Y_{it} = & \alpha_{it} + \phi Y_{i,t-1} + \rho \Delta Y_{i,t-1} + \beta_U U_{it} + \beta_{uv}(v_{i,t-1} U_{it}) + b_{01} \sum_z F_{zit} + b_{02} \sum_z v_{i,t-1} F_{zit} \\ & + b_{11} \sum_z g_1(Z) F_{zit} + b_{12} \sum_z g_1(Z) v_{i,t-1} F_{zit} + b_{21} \sum_z g_2(Z) F_{zit} + b_{22} \sum_z g_2(Z) v_{i,t-1} F_{zit} + \varepsilon_{it} \end{aligned} \quad (4)$$

I estimate the equation separately for each quintile of market capitalization using the level of lagged institutional ownership ( $Y_{i,t-1}$ ) as the interaction variable  $v$ . The standard errors are robust in presence of heteroscedasticity (White's correction), autocorrelation (Newey-West), and cross-sectional correlation, following procedures suggested in Petersen (2007). Clustering by firms, clustering by time, and adjusted

Fama-MacBeth method all gave similar results<sup>24</sup>.

One drawback of this approach is that it is an aggregate measure of all institutional daily flows, so it can not identify the types of institutions. Thomson Financial 13F data provides the categorization of institutional types, so I modified the CRS approach to separate the order flows according to the institutional investor types filed by Thomson Financial. All else being equal, I estimate the following equation:

$$\Delta Y_{i,j,t} = \alpha + \gamma Y_{i,j,t-1} + \phi(L)(\Delta Y_{i,j,t}) + \beta_U U_{i,j,t} + \sum_z \beta_{FZ} F_{Zi,j,t} + \varepsilon_{i,j,t} \quad (5)$$

For each  $j=1, \dots, 5$ , where  $j$  is the type of institution,  $\phi(L)$  is a lag polynomial to define the lagged values of  $\Delta Y_{i,j,t}$ . From the estimated parameters I infer the daily net trading flows for each institutional investor type, using a procedure similar to that used previously. For a robustness check, I add institutional types to equation (3) and (4) and estimate the parameters and generate institutional order flows for each institution type; the results are not affected qualitatively.

Following CRS, I construct the daily institutional flows in a similar equation:

$$\begin{aligned} \Delta Y_{id} = & \alpha_d + \phi_d Y_{i,t-1} + \rho_d \Delta Y_{i,t-1} + \beta_d U_{id} + \beta_{\alpha}(Y_{i,t-1} U_{id}) + b_{01} \sum_z F_{zid} + b_{02} \sum_z Y_{i,t-1} F_{zid} \\ & + b_{11} \sum_z g_1(Z) F_{zid} + b_{12} \sum_z g_1(Z) Y_{i,t-1} F_{zid} + b_{21} \sum_z g_2(Z) F_{zid} + b_{22} \sum_z g_2(Z) Y_{i,t-1} F_{zid} + \varepsilon_d \end{aligned} \quad (6)$$

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<sup>24</sup> When regressing changes of quarterly ownership on buy/sell/unclassified volume, I include lags of ownership, and try clustering by quarters and clustering by firms. The results are qualitatively the same.

The assumption for aggregating daily institutional flow equation (6) up to the quarterly frequency equation (4) is that “the error in measured daily institutional ownership  $\varepsilon_{id}$  is uncorrelated at all leads and lags within a quarter with all of the right hand side variables in equation (6). This exogeneity assumption guarantees that the parameters of the daily function  $b_{01}$ ,  $b_{02}$ ,  $b_{11}$ ,  $b_{12}$ ,  $b_{21}$ ,  $b_{22}$  and  $\tau$  will be the same as those estimated at the quarterly frequency.” From equation (4) I estimate the parameters and recover the parameters of equation (6), then finally construct the predicted value  $E_d[\Delta Y_{id}]$  for each stock  $i$  for each day  $d$ , as a percentage of CRSP daily shares outstanding. I multiply it by the CRSP daily shares outstanding to get my institutional daily flow measure – Daily Net Buying Dollar Imbalance. The quarterly parameters ( $\rho$ ,  $\phi$ ,  $\alpha$  and  $\varepsilon$ ) are not incorporated into the daily level to avoid ad-hoc assumptions, so the values of these parameters are set to zero at the daily level. I repeat the same procedures for different institutional types and different firm sizes.